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'

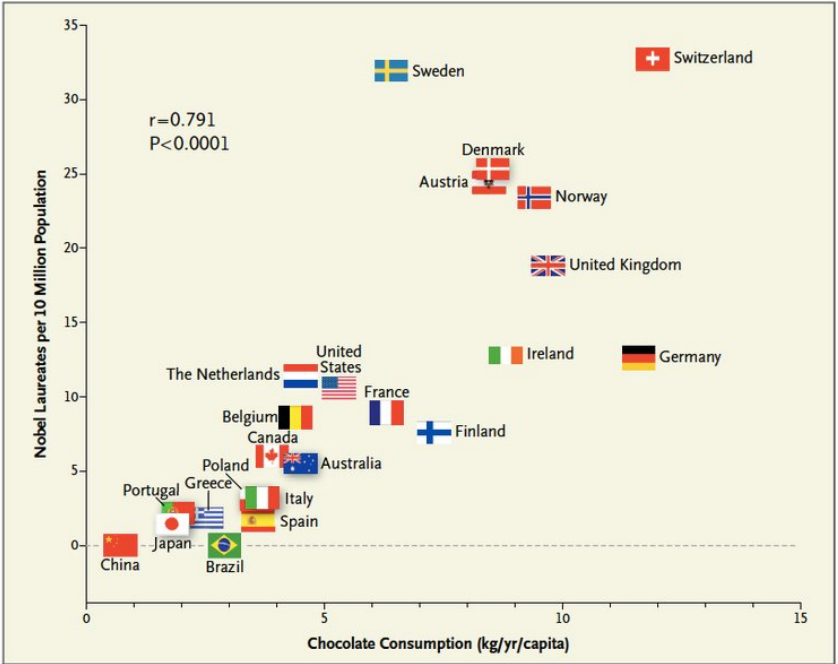

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

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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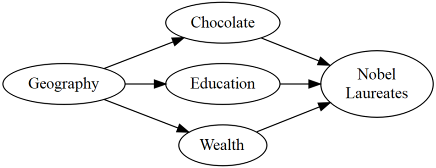

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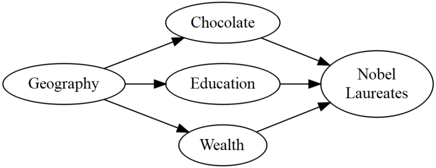

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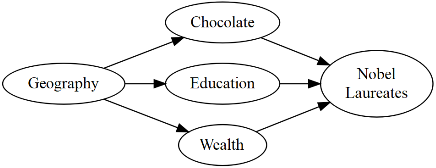

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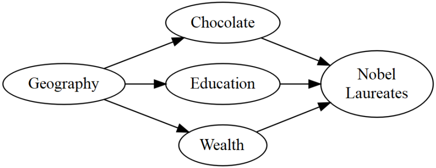

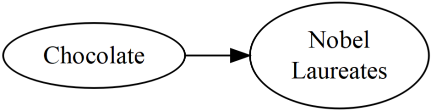

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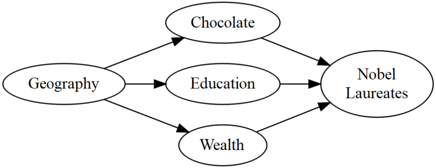

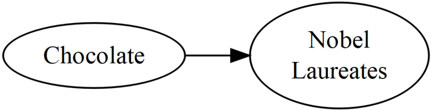

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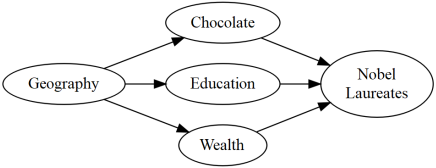

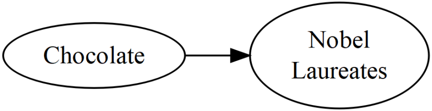

- Identifying the source of **ALL** of the variation in Nobel Laureates
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- Identifying how much **ONE** variable causes variation in Nobel Laureates
- This we can do!

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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Proababilistic Explanation

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- Treatment effects are a distribution, not a single value

Section 2

Causal Inference

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- 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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  - Would Brazil have won the 2014 World Cup if Neymar had not been injured?

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

Causal Inference

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Average Treatment Effect

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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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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

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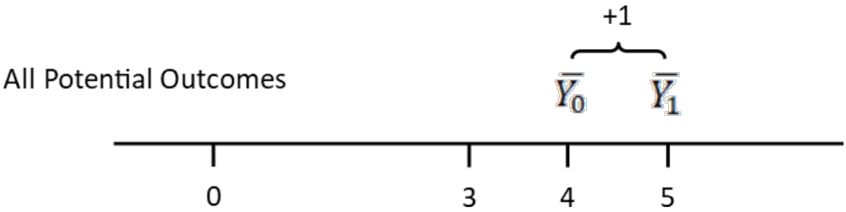

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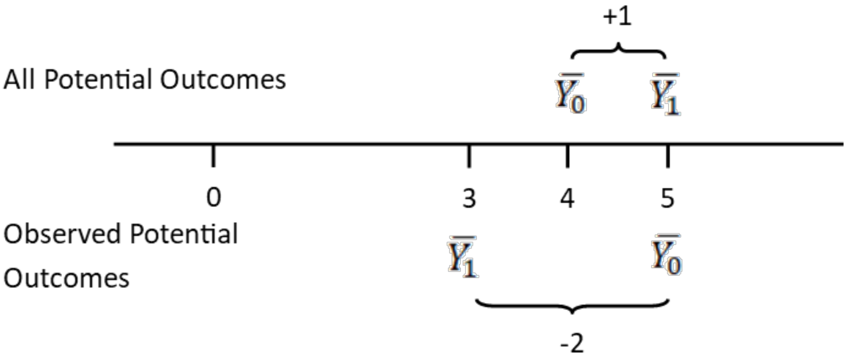

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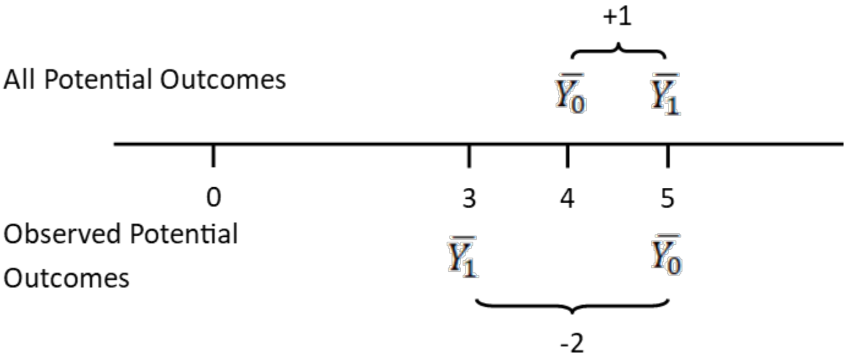

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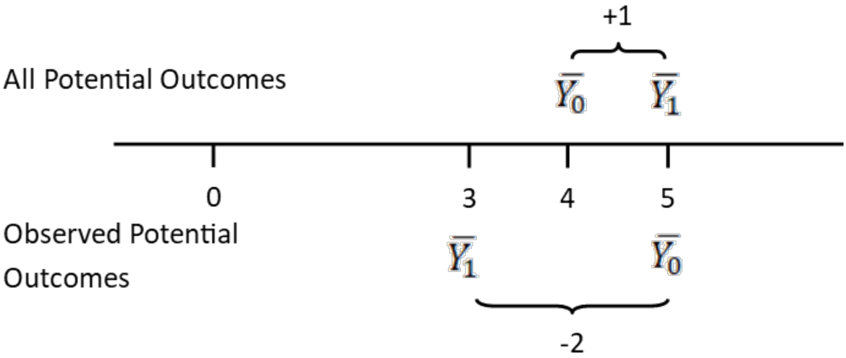

- $E(Y_1)$ values are **biased lower** in the observed data
- $E(Y_0)$ values are **biased higher** in the observed data
- So $E(Y_1) - E(Y_0)$ is **biased**

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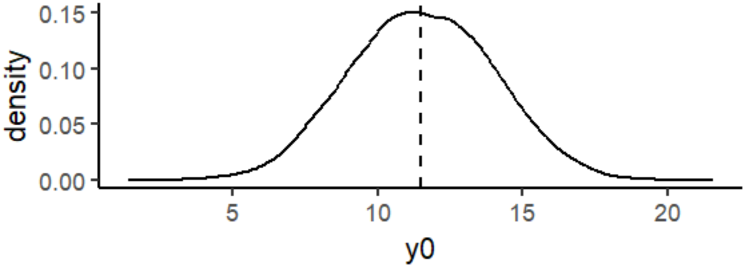

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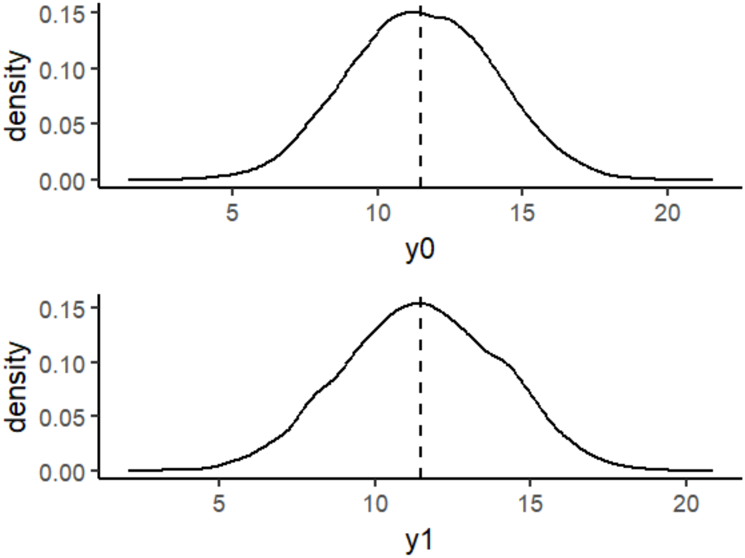

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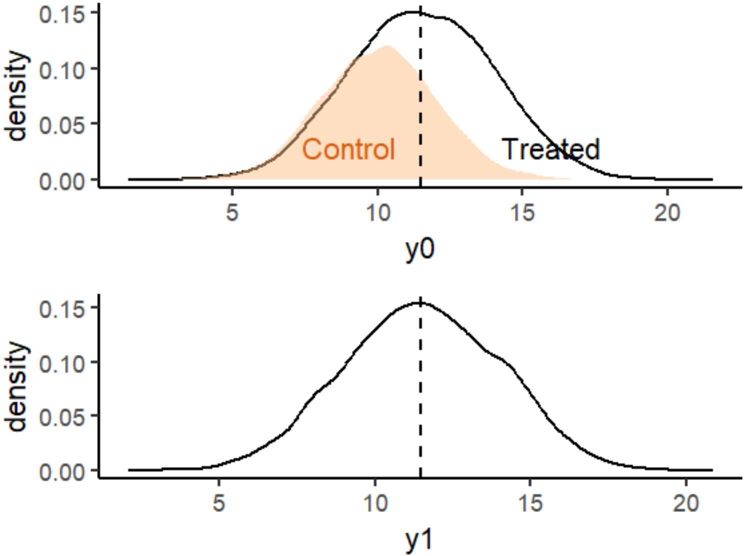

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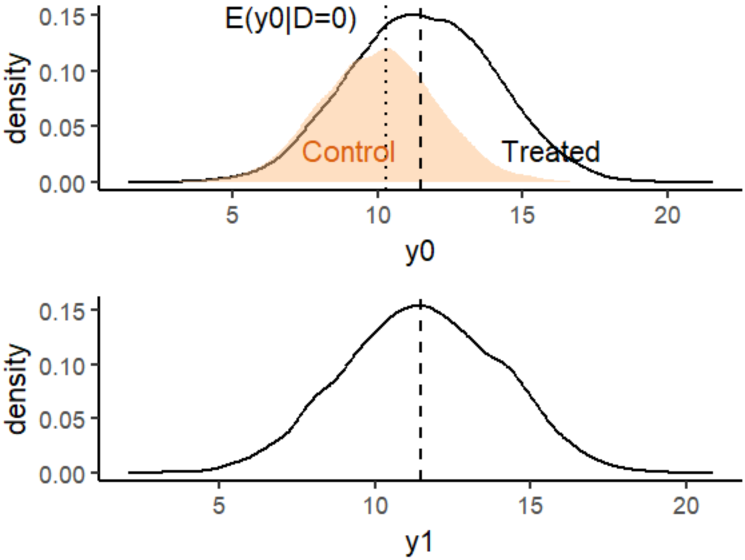

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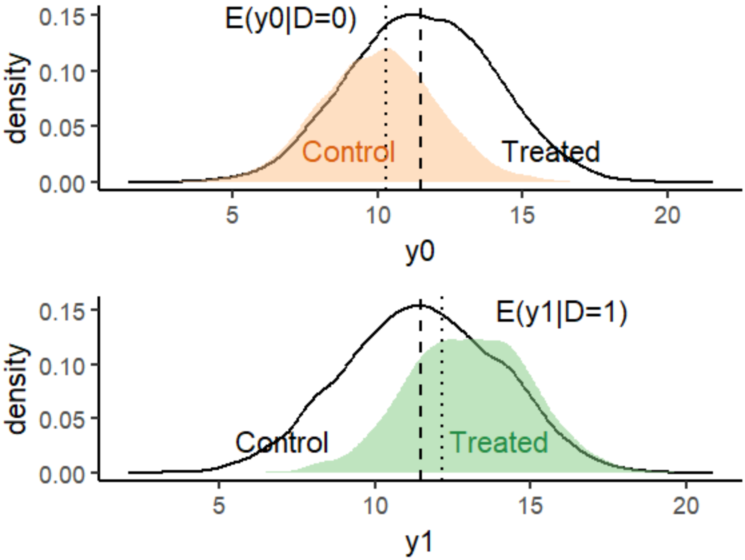


Section 3

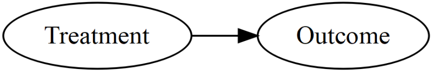
Why Observational Data is Biased

Bias

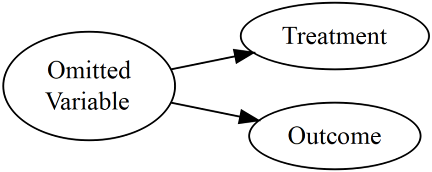
- Why are potential outcomes biased in our data?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- **In all of these cases the potential outcomes are distorted so basic regression is biased**

Omitted Variable Bias

A real causal relationship:



Being misled by omitted variable bias:



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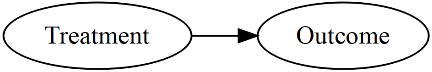

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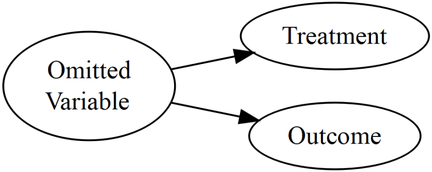

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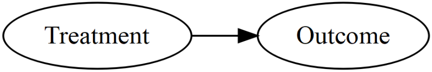

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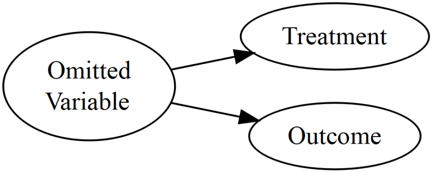

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

Omitted Variable Bias

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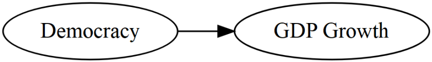

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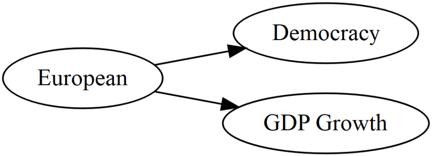

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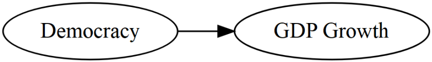

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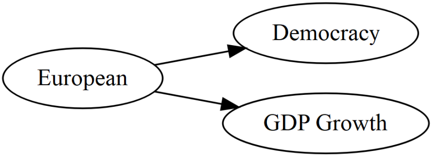

- European countries faced conditions that encouraged both democracy and rapid GDP growth

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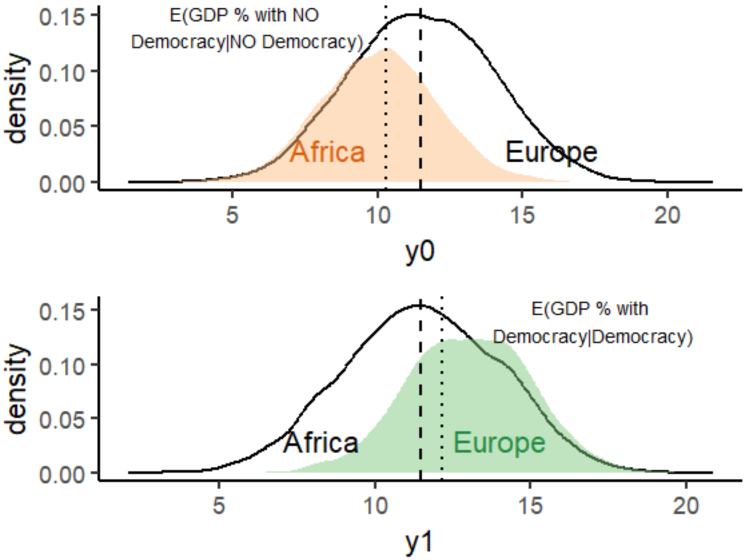
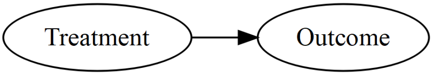


Reverse Causation

A real causal relationship:



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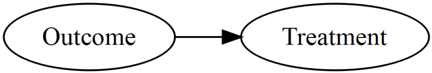

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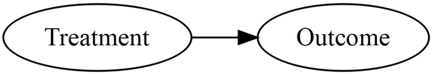

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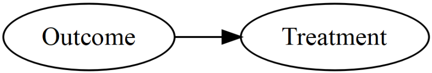

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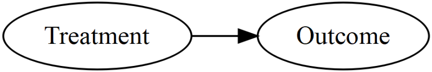

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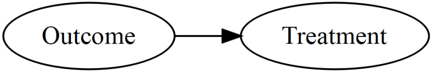
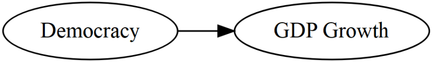


- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are correlated

Reverse Causation

A real causal relationship:



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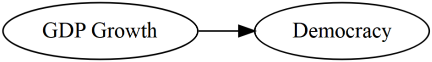

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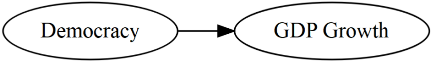

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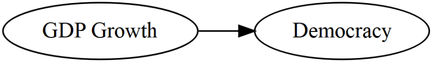
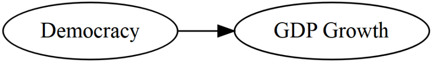


- GDP Growth encourages democratization

Reverse Causation

A real causal relationship:



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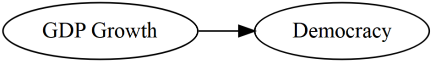
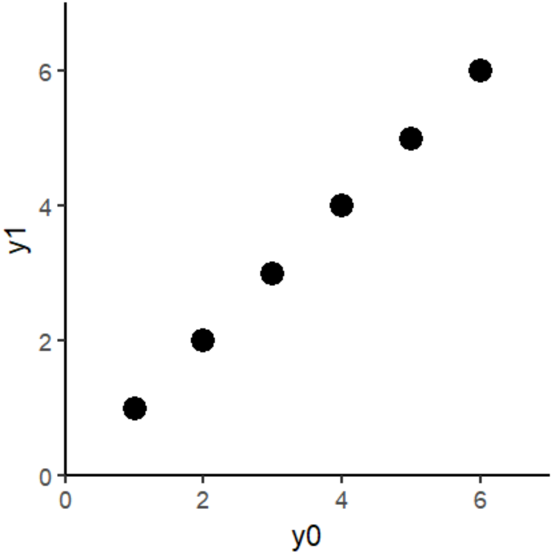


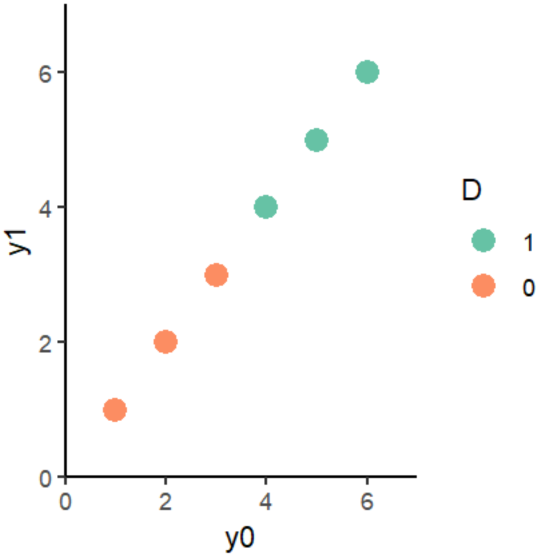
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation



- $E(Y_1 - Y_0) = 0$

Reverse Causation



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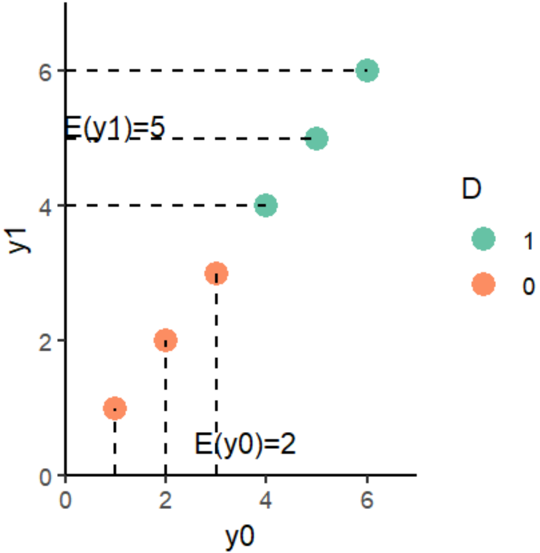

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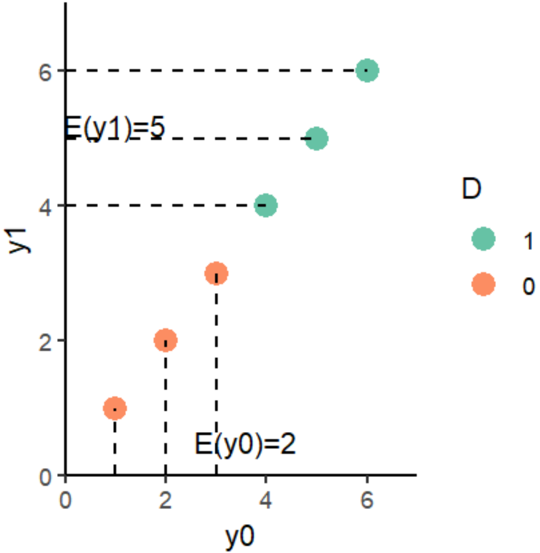

- $E(Y_1|D=1)-E(Y_0|D=0)=5-2=3$

Selection Bias

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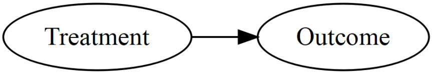

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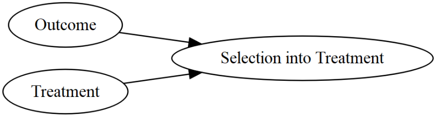

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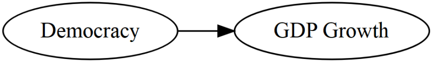

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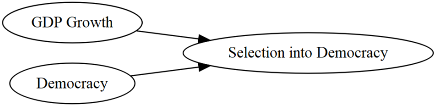

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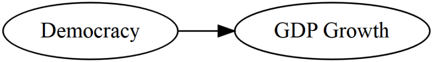

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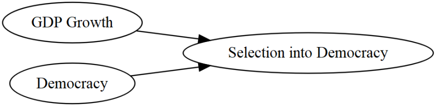

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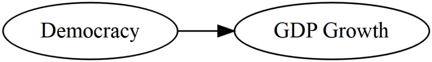

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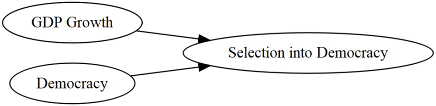
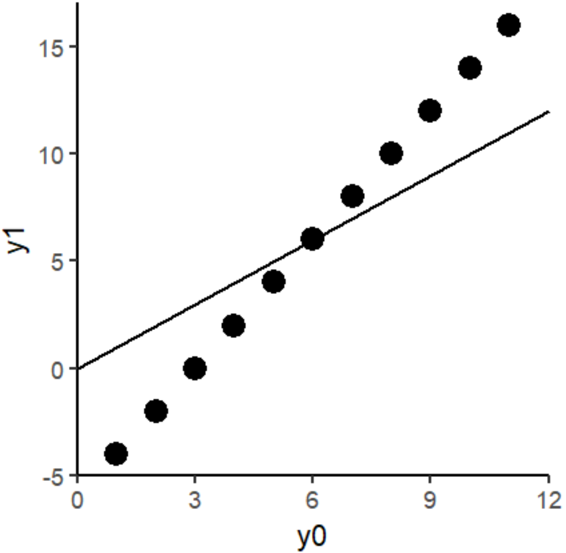


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Self-Selection Bias



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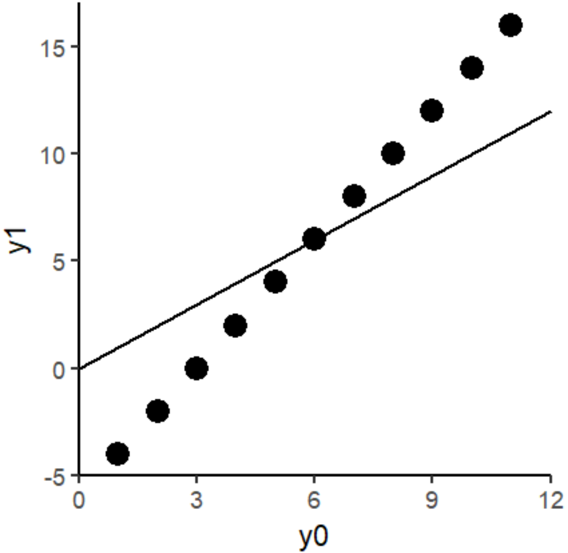
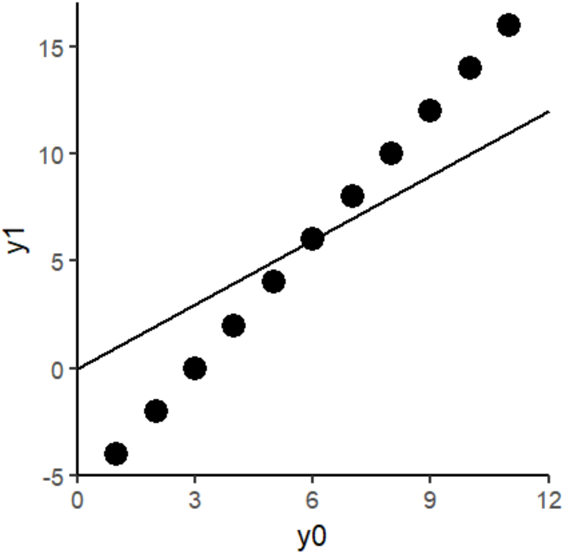


- Countries which can boost their GDP growth by becoming a

Self-Selection Bias



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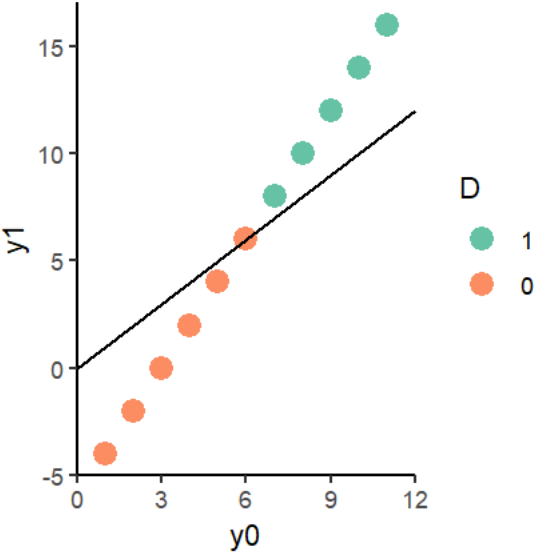

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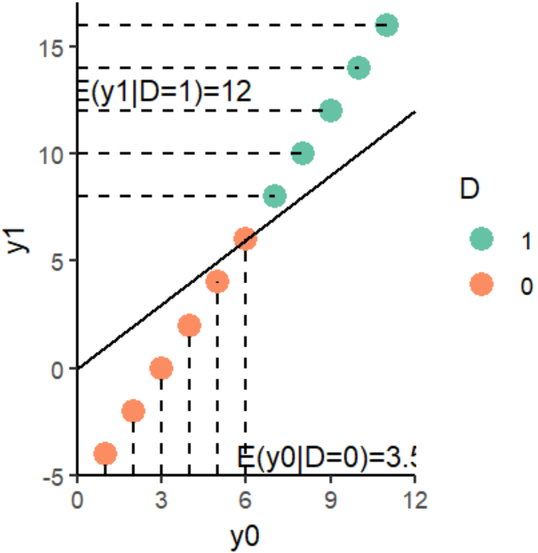
Self-Selection Bias



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

Causal Inference

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  - It means our comparison control cases are really misleading
  - 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

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Treatment Assignment Mechanism

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

Causal Inference

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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 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

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