

FLS 6441 - Methods III: Explanation and Causation

Week 2 - A Framework for Explanation

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Section 1

Explanation

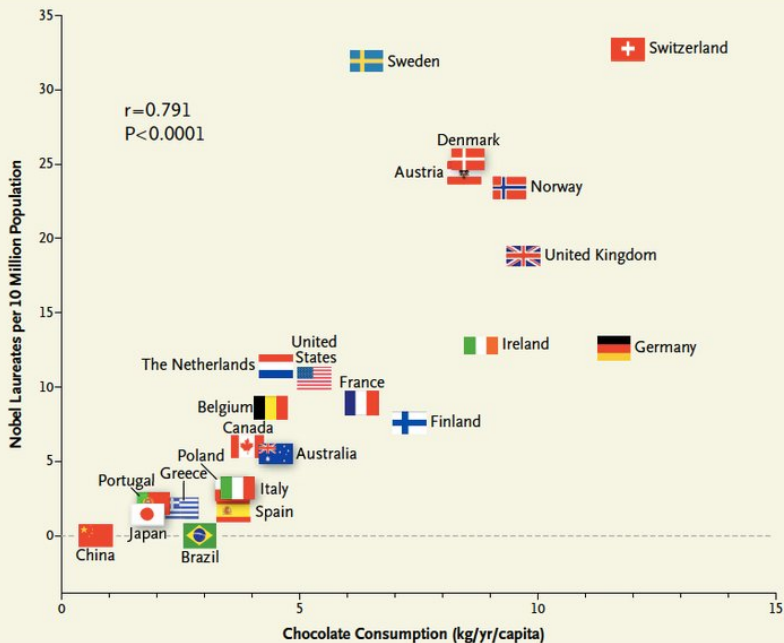


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Explanation

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- ▶ 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
 - ▶ 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

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Explanation

- ▶ What does it mean to explain something?
- ▶ To give an account of what happens, *and why*
 - ▶ The 'chain of causation'
- ▶ If D explains y , we are saying that the *absence* of D would have led to a different value of y
- ▶ There exists a 'counterfactual' possibility that did not happen

Explanation

Deterministic Explanation

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Every time D happens, Y happens

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Probabilistic Explanation

- ▶ If D happens, the **probability** of Y increases
- ▶ Treatment effects are a distribution, not a single value

Explanation

- ▶ Two perspectives on explanation:

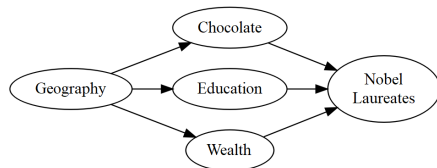
Explanation

- 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? |
| Backward-looking | Forward-looking |

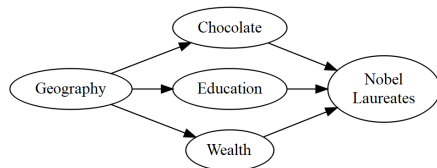
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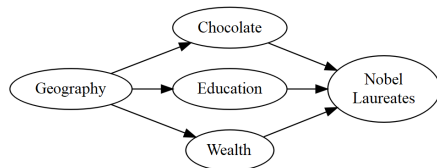
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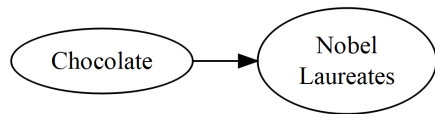
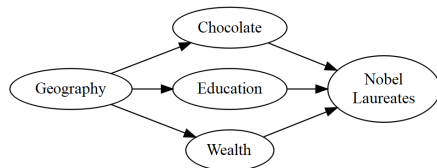
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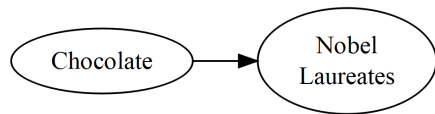
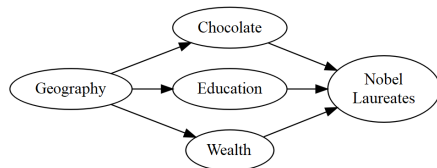
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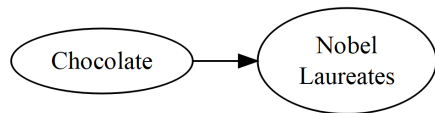
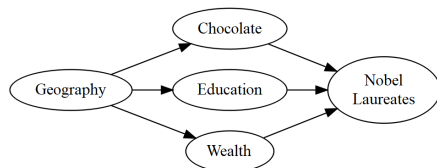
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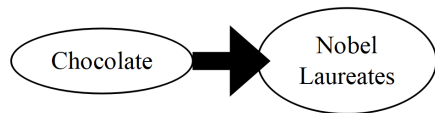
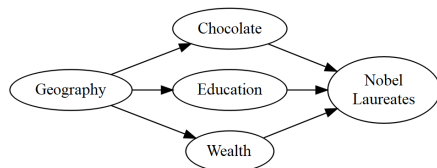
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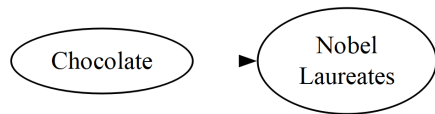
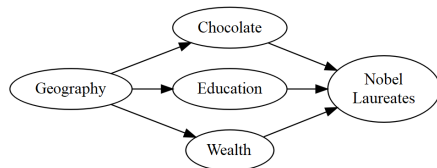
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- ▶ AND to clearly define a '**Control**'
 - ▶ What is the opposite of investing \$1bn in education?
 - ▶ No investment, or investing it elsewhere?
- ▶ Define treatment:

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

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- ▶ So we usually want to study a **single outcome**

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 - ▶ But our analysis needs to take account of the 'clustered' treatment
- ▶ Units are **time-specific**: the same person 10 minutes later is a different unit

Section 2

Causal Inference

Causal Inference

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

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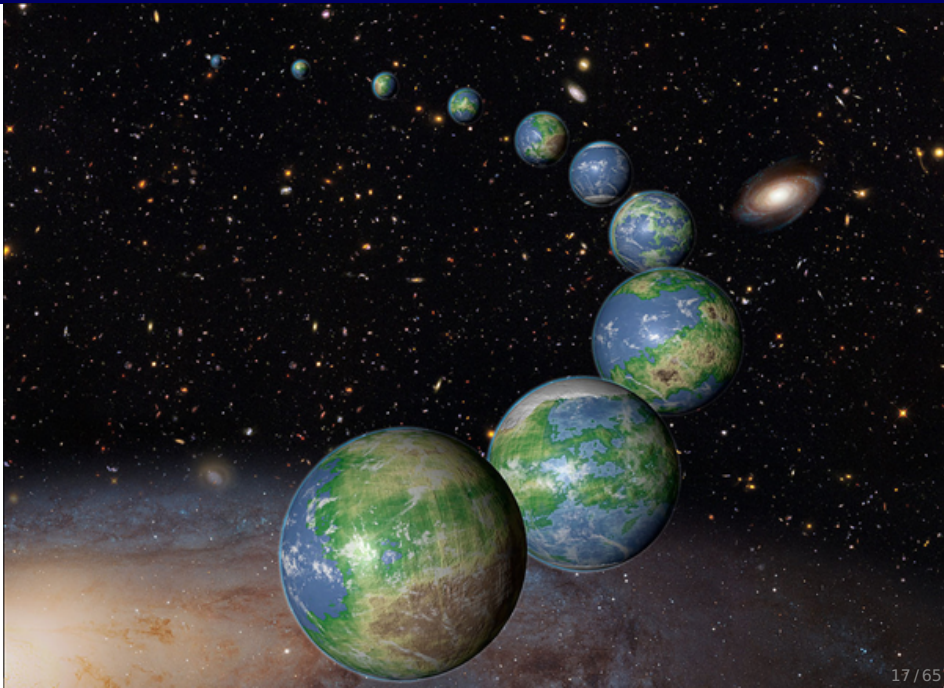
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Causal Inference

Potential Outcomes are just another Variable for each Unit

| | 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 |
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| Colombia | 7 | 7 | 0 |
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$$ATE = E(\alpha_i) = E(Y_1 - Y_0) = E(Y_1) - E(Y_0) = \frac{\sum_i (Y_{1i} - Y_{0i})}{N}$$

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$$ATU = E(\alpha_i | D = 0) = E(Y_1 - Y_0 | D = 0) = \frac{\sum_i (Y_{1i} - Y_{0i} | D=0)}{N_{Control}} \quad (2)$$

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

Causal Inference

Potential Outcomes Example

| | Democracy? | GDP Growth if Democracy | GDP Growth if NOT Democracy | Treatment Effect |
|-----------|------------|-------------------------|-----------------------------|------------------|
| | D_i | Y_1 | Y_0 | $Y_1 - Y_0$ |
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| | | | | |
| | | | | |
| ATT | 1 | 3 | 2.5 | 0.5 |

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| ATU | 0 | 6.3 | 5 | 1.3 |

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

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

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

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| | Democracy? | GDP Growth if Democracy | GDP Growth if NOT Democracy | Observed GDP Growth |
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| Average Treatment Effect | | 3 | 5 | -2 |

Causal Inference

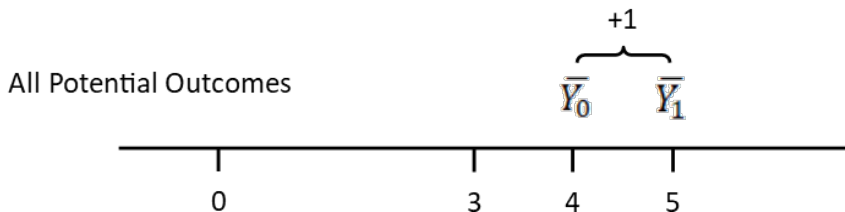
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Causal Inference

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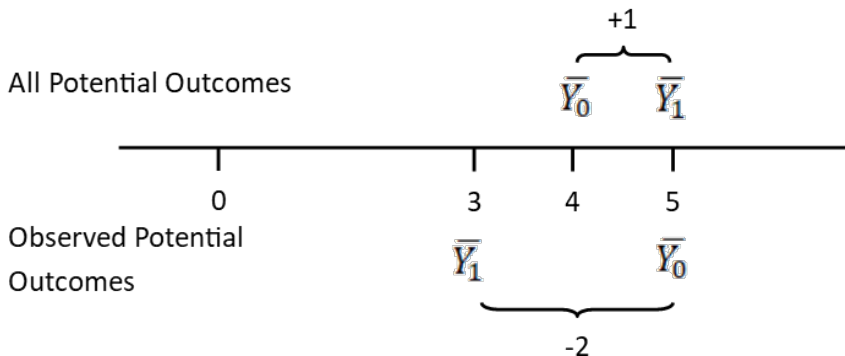
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Causal Inference

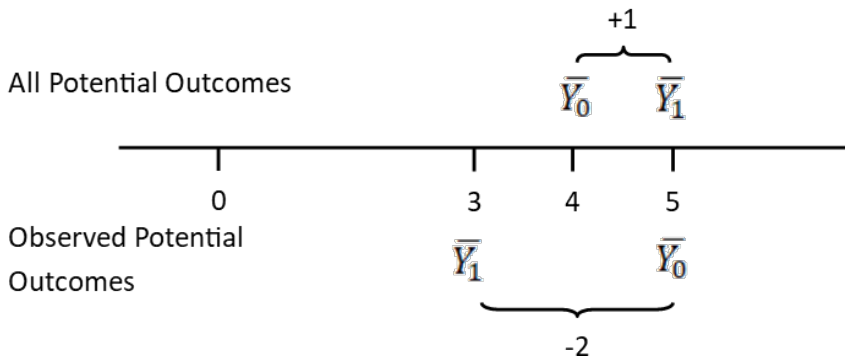
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Causal Inference

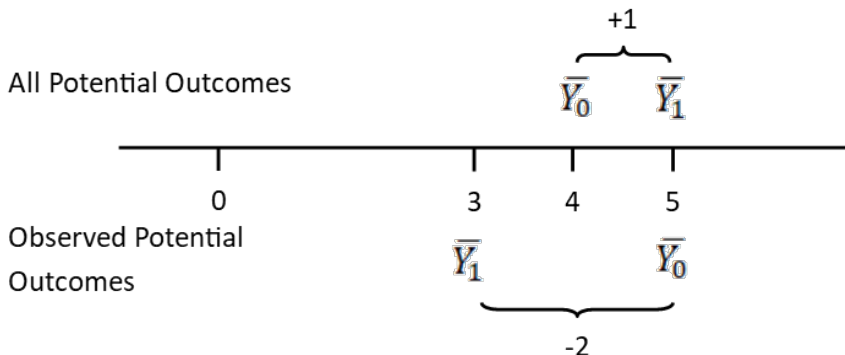
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Causal Inference

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Causal Inference

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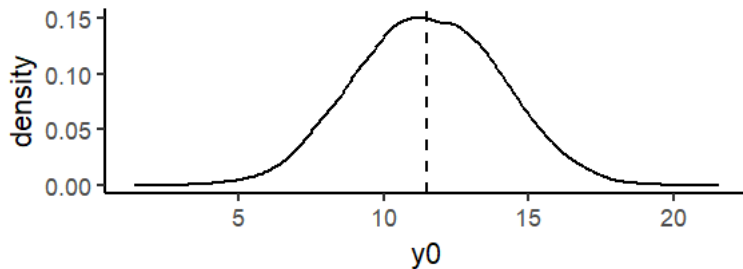
Causal Inference

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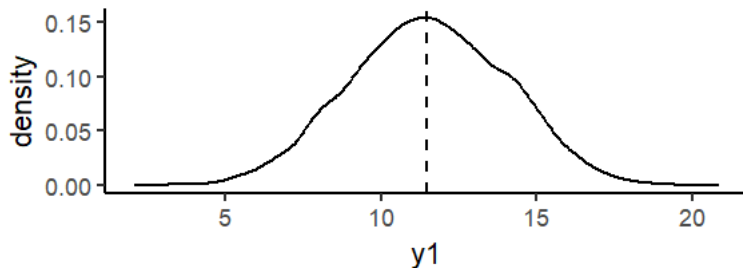
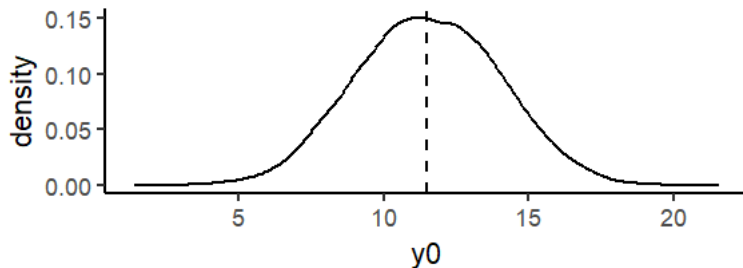
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 - ▶ Counterfactuals are not **plausible**
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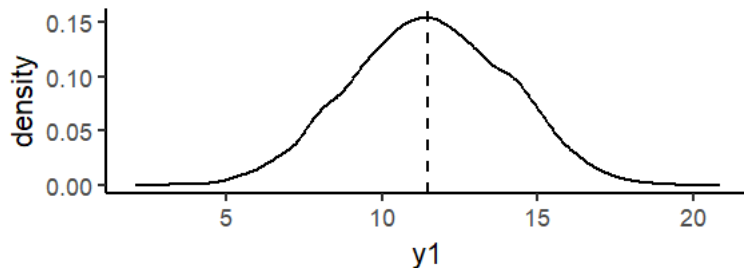
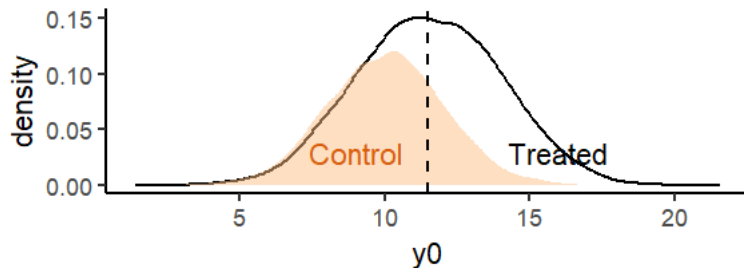
Causal Inference



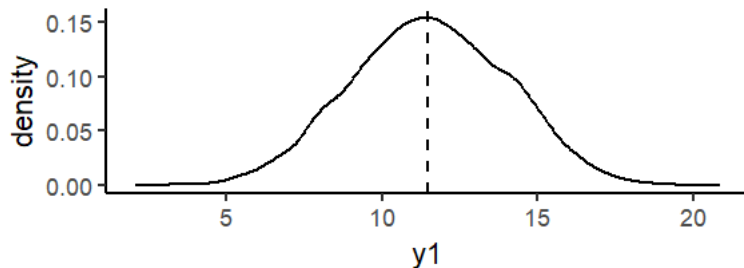
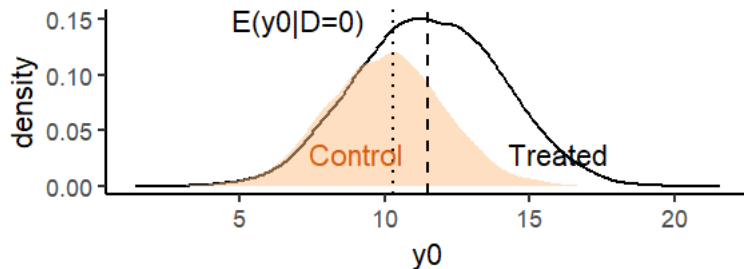
Causal Inference



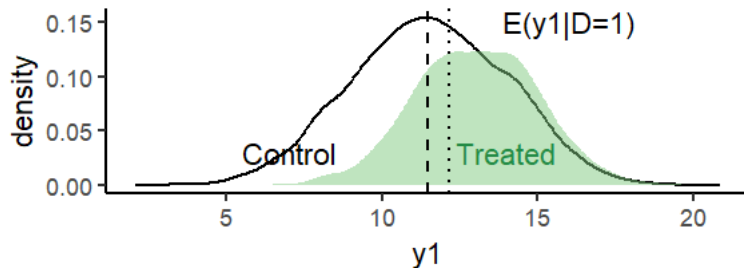
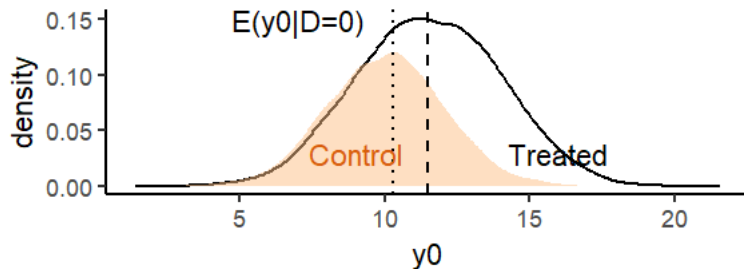
Causal Inference



Causal Inference



Causal Inference



Causal Inference

- Lots of averages:

| | | Hypothetical outcome | |
|------------------|---------|----------------------|-------------------|
| | | Y_0 | Y_1 |
| Actual Treatment | $D = 0$ | $E(Y_{0i} D = 0)$ | $E(Y_{1i} D = 0)$ |
| | $D = 1$ | $E(Y_{0i} D = 1)$ | $E(Y_{1i} D = 1)$ |

Causal Inference

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| | | Hypothetical outcome | |
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| | | Y_0 | Y_1 |
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Causal Inference

- All our causal estimates are **averages**

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

Causal Inference

- All our causal estimates are **averages**
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| | No Average Effect $E(Y_1 - Y_0) = 0$ | "Sharp null": No individual effects $(Y_{1i} - Y_{0i} = 0)$ |
|----------------|---|--|
| Brasil | 2 | 0 |
| Argentina | -1 | 0 |
| Bolivia | 1 | 0 |
| Colombia | 0 | 0 |
| Peru | -2 | 0 |
| Average | 0 | 0 |

Section 3

Why Observational Data is Biased

Bias

- Why are potential outcomes biased in our data?

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
 2. Reverse Causation

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
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 3. Selection Bias

Bias

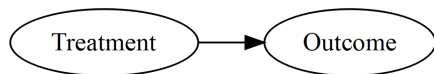
- ▶ Why are potential outcomes biased in our data?
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Bias

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

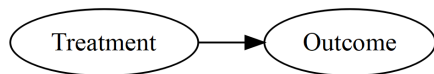
Omitted Variable Bias

A real causal relationship:

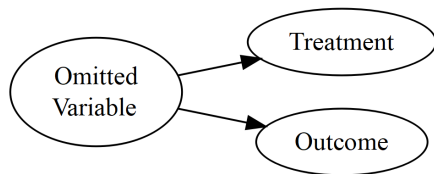


Omitted Variable Bias

A real causal relationship:

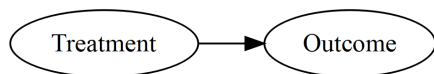


Being misled by omitted variable bias:

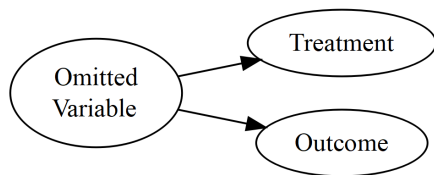


Omitted Variable Bias

A real causal relationship:



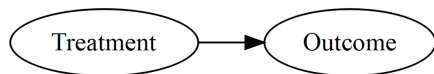
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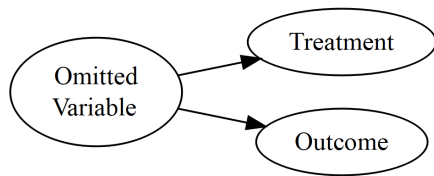
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

Omitted Variable Bias

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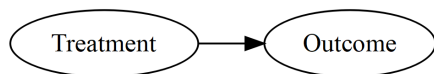
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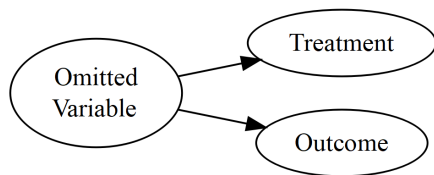
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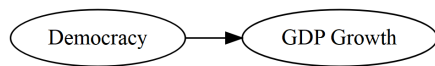
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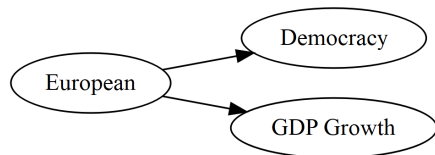
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- ▶ So treated units have non-representative Y_1
- ▶ And control units have non-representative Y_0

Omitted Variable Bias

A real causal relationship:

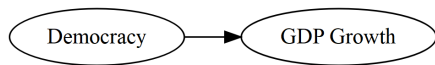


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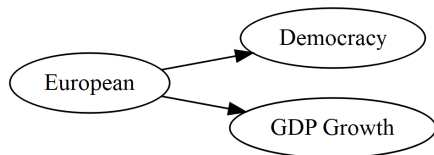


Omitted Variable Bias

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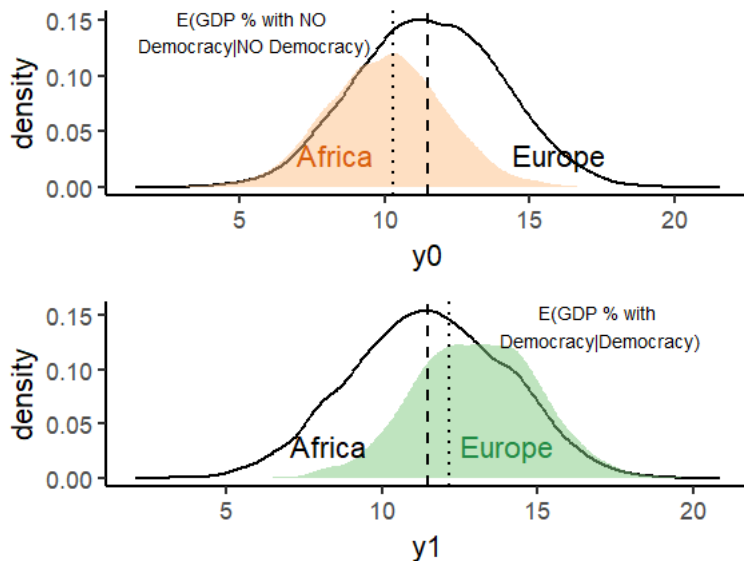


Being misled by omitted variable bias:



- ▶ 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

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

Omitted Variable Bias

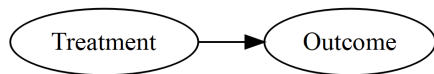
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$$\hat{ATE} = E(Y_1|D=1) - E(Y_0|D=0)$$

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

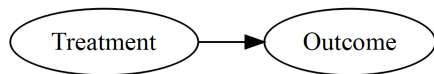
Reverse Causation

A real causal relationship:

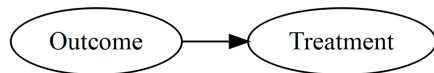


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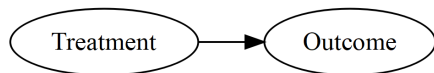


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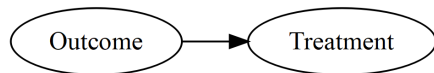


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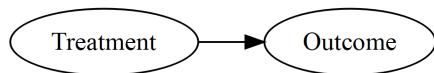
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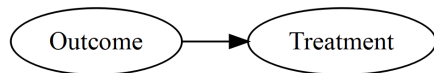
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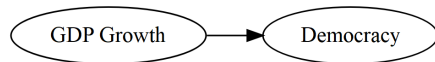
- ▶ D does not affect Y , but higher Y makes treatment (D) more likely
- ▶ So the two variables are **correlated**

Reverse Causation

A real causal relationship:

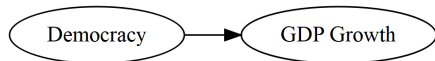


Being misled by reverse causation:

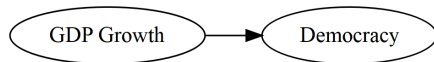


Reverse Causation

A real causal relationship:



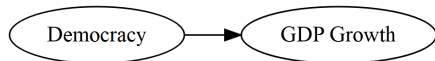
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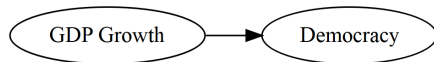
- GDP Growth encourages democratization

Reverse Causation

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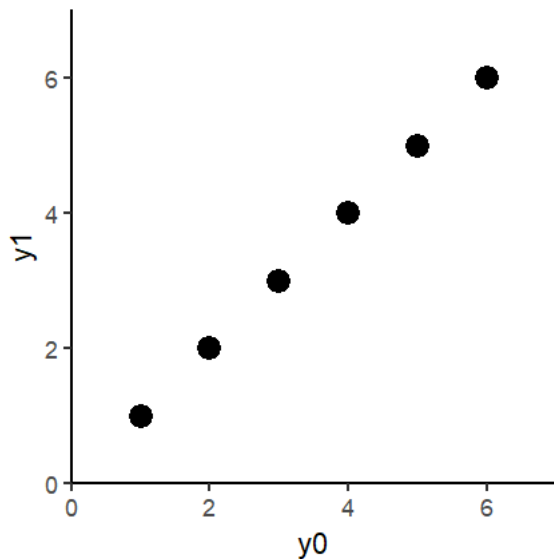


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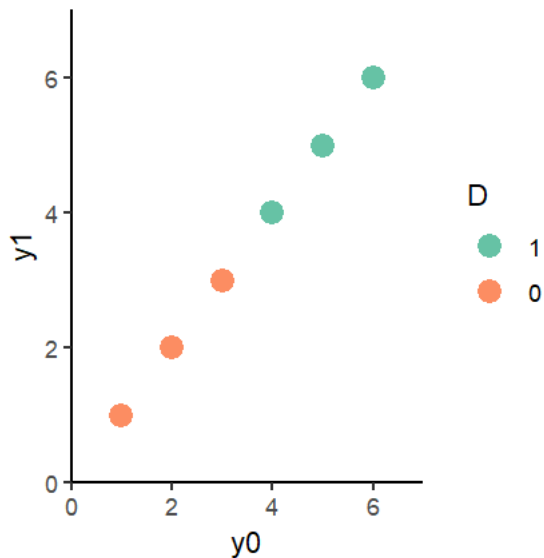
- ▶ GDP Growth encourages democratization
- ▶ So democracies are more likely to have experienced high growth rates

Reverse Causation

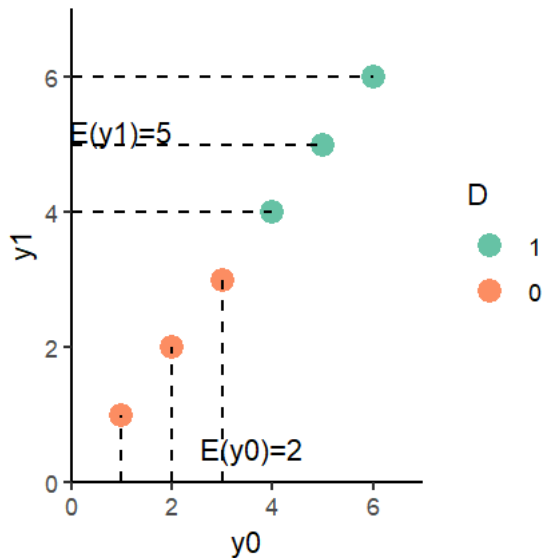


► $E(Y_1 - Y_0) = 0$

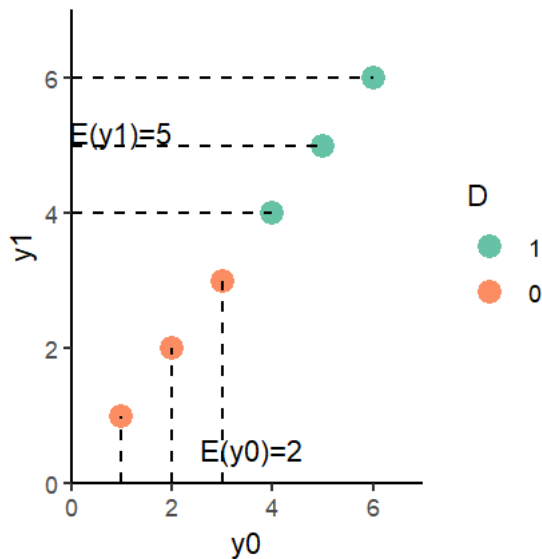
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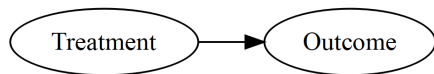
Reverse Causation



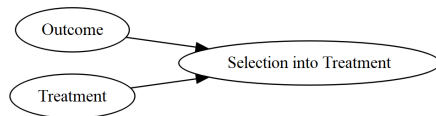
► $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:

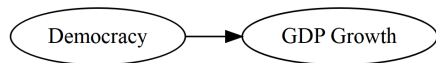


Being misled by Selection Bias:

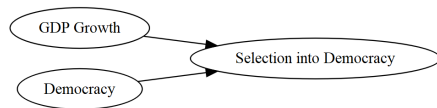


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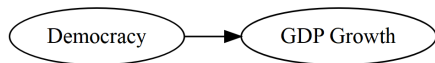


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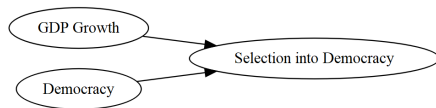


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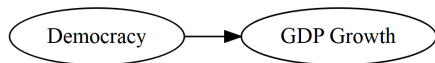
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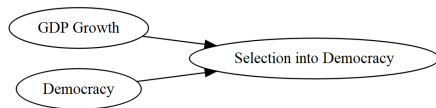
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

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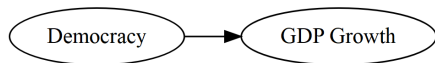
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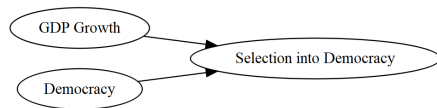
- ▶ The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- ▶ We don't see any of the low y_1 's of units which avoid treatment

Selection Bias

A real causal relationship:



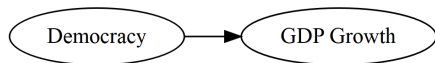
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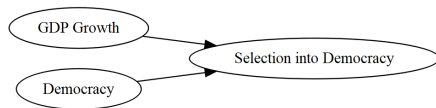
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Selection Bias

A real causal relationship:

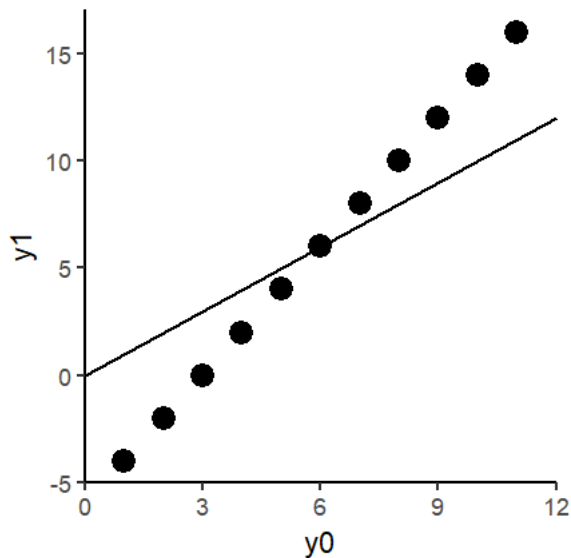


Being misled by Selection Bias:

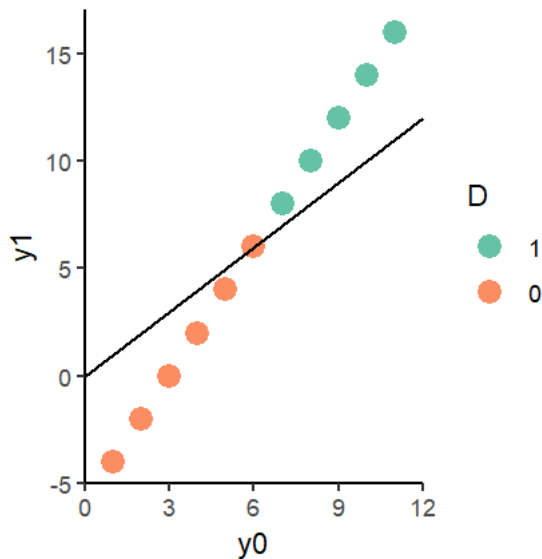


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 - ▶ Countries which can boost their GDP growth by becoming a democracy choose to democratize
 - ▶ Ex. Mexico? Myanmar?

Self-Selection Bias

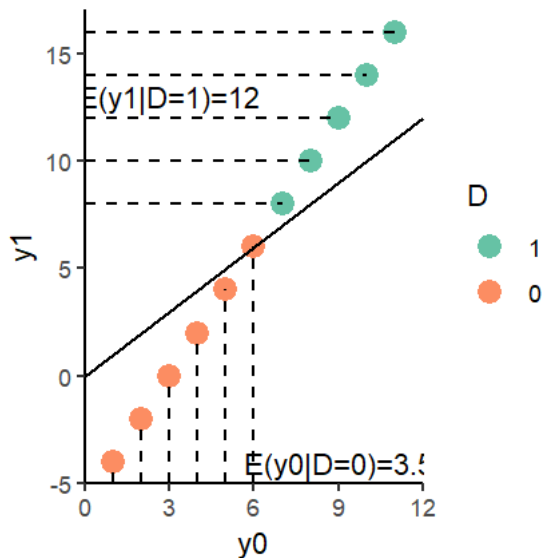


Self-Selection Bias



► $E(y_1) - E(y_0) = 0$

Self-Selection Bias



► $E(y_1|D=1) - E(y_0|D=0) = 8.5$

Self-Selection Bias

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

Self-Selection Bias

- Allow treatment effects to vary across individuals, so

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$$\underbrace{E(Y_i|D=1) - E(Y_i|D=0)}_{\text{Observed Effect}} = \underbrace{E(Y_{1i} - Y_{0i})}_{\text{Real ATE}}$$

$$+ \underbrace{\frac{1}{2} [E(Y_{1i}|D=1) - E(Y_{1i}|D=0)]}_{\text{Imbalance on } Y_1} + \underbrace{\frac{1}{2} [E(Y_{0i}|D=1) - E(Y_{0i}|D=0)]}_{\text{Imbalance on } Y_0} \quad (3)$$

NB: For equal-sized treatment and control groups

Self-Selection Bias

- Allow treatment effects to vary across individuals, so

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NB: For equal-sized treatment and control groups

Treatment Assignment Mechanism

- In all of these cases, **which units receive 'treatment' ($D_i = 1$)**, and why, affect our estimate of the relationship between D and Y

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

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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 Soya, 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.

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Section 4

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 - ▶ **Design-Based Solutions** to the Fundamental Problem of Causal Inference: Which treatment assignment mechanisms **avoid these biases** and provide plausible counterfactuals
 - ▶ How much can we learn with better research design?
 - ▶ **Model-Based Solutions:** Not so much.

Rest of the Course

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