Making Causal Critiques

Day 2 - Fundamental Critiques

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- Proportional Representation electoral systems have more parties
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- Development helps democracies endure
- ...And that's about it

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  - Many add **descriptive** knowledge
  - Many investigate **specific** events, not generalizable variables
  - Many highlight **correlations** between variables

Learning from Data

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- But the only way to *confirm* the hypothesis is to verify that:
  1. In other cases, the presence of the condition also produces the same outcome (if not, the explanation is not sufficient)
  2. The absence of the condition does not produce the same outcome (if not, the explanation is not necessary)

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  - But...Costa Rica

Learning from Data

- For example, we could look at India and conclude large Asian countries produce successful democracies
  - But...China
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- Only by looking at other cases, particularly 'control' cases (small non-Asian countries) can we understand if this explanation is plausible

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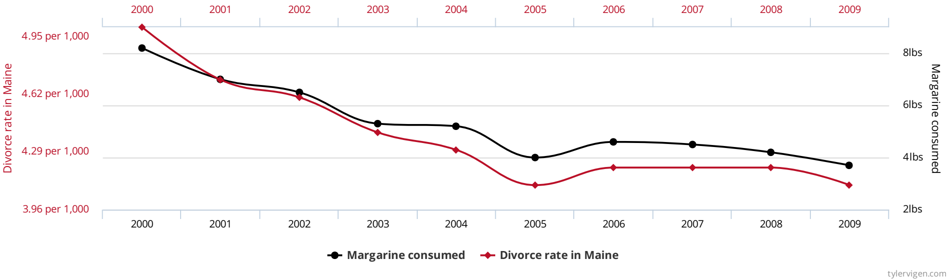
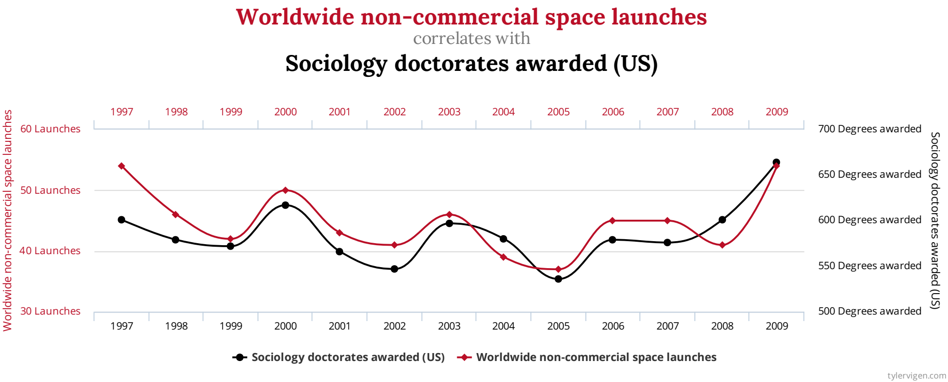
- *More* data will not help
- The problem is the *type* of data; it does not allow us to answer the causal question

Divorce rate in Maine
correlates with
Per capita consumption of margarine




Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
60 Launches
50 Launches
40 Launches
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650 Degrees awarded
600 Degrees awarded
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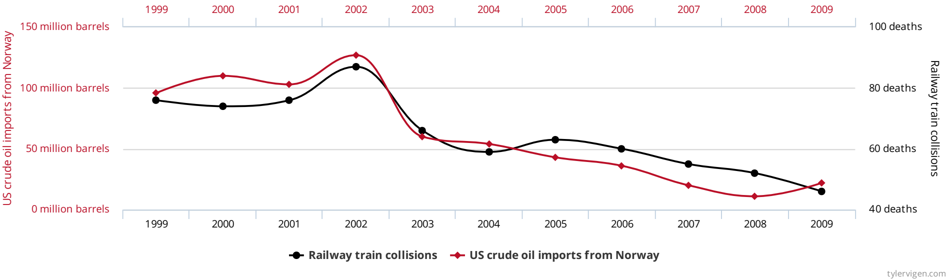
Worldwide non-commercial space launches
tylervigen.com

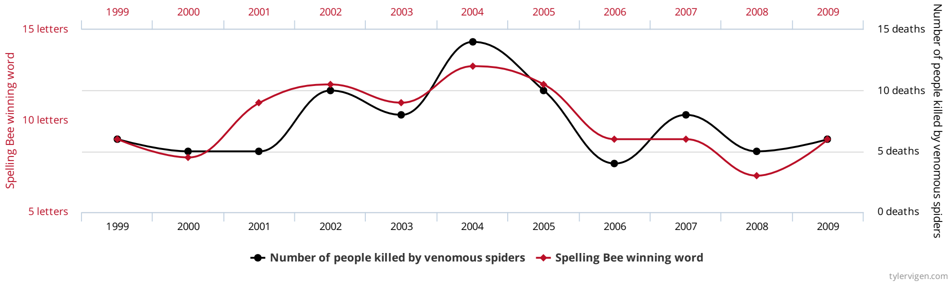
US crude oil imports from Norway

correlates with

Drivers killed in collision with railway train



Letters in Winning Word of Scripps National Spelling Bee
correlates with
Number of people killed by venomous spiders



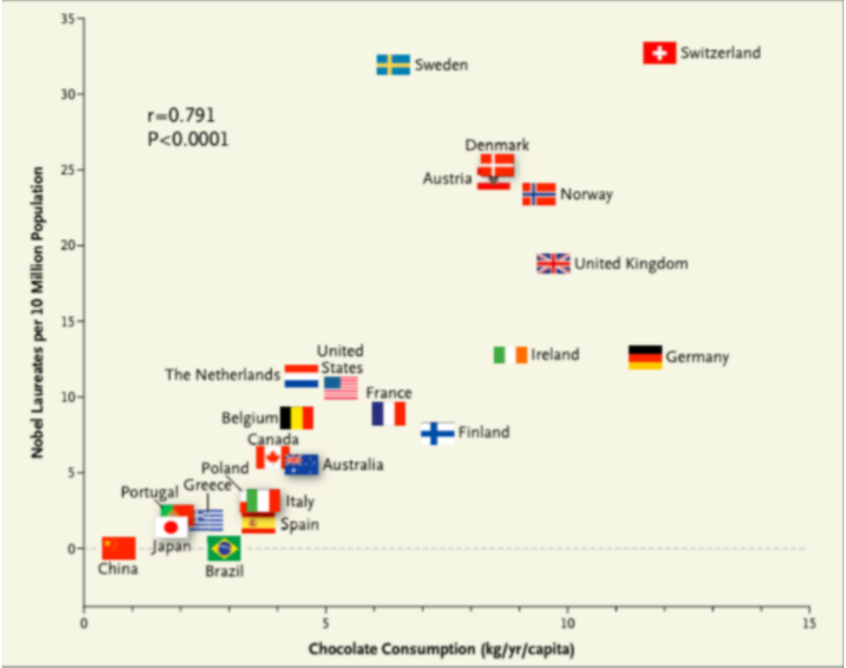


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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  - For *prediction*, correlation is fine: If we know a country has chocolate consumption of 10kg/yr/capita we can confidently 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
- So if we want to provide policy-relevant advice, we need to know more than just correlation

Learning from Data

- Why isn't correlation enough?
    - 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 means identifying the *direct* and *local* factors that generate Nobel Laureates

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  - The data shows no-one lies on their tax forms
  - So let's abandon tax checks; the government wants to save money
  - But reducing checks reduces the chances of getting caught
  - Citizens start to lie on their tax forms
- That means we need to understand what *causes* people to lie on tax forms, so we can better understand their behaviour

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Causes of Effects	**Effects of Causes**
What caused Y?	Does X cause Y?
Why did the United States grow faster than Bolivia in the twentieth century?	Did the more permanent colonial settlement of the United States compared to Bolivia affect their subsequent growth rates?

Causal Inference

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- AND to clearly define a control
  - What is the opposite of investing $1bn in education?
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- Define treatment:

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

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  - Tempting to look at many outcomes, but the risk of cherry-picking
    - If we study 20 outcomes, on average one will show a significant effect even with no real causal effect

Causal Inference

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

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- The **causal effect** of treatment is how each unit's outcome differs when it is treated and not treated
- This means comparing the **potential outcomes** for unit i:

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

- Treatment Effect $= Y_{1i} - Y_{0i}$

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- To explain a class of events - not a single event - we need multiple counterfactual comparisons

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- eg. how a proportional representation electoral system affects investment in education
  - The **treatment** is a change to a PR electoral system (vs FPTP)
  - The **outcome** is the level of investment in education

Causal Inference

Potential Outcomes Example

	Investment in Education if PR	Investment in Education if NOT PR	
	Y_1	Y_0	Treatment Effect
Brasil	8	4	4
Argentina	10	7	3
Bolivia	2	4	-2
Colombia	11	11	0
Peru	6	2	4

Causal Inference

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  - No units can receive **both** treatment and control

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

Causal Inference

Potential Outcomes Example

	PR System?	Investment in Education if PR	Investment in Education if NOT PR	
	D_i	Y_1	Y_0	Treatment Effect
Brasil	1	8	?	?
Argentina	1	10	?	?
Bolivia	0	?	4	?
Colombia	0	?	11	?
Peru	0	?	2	?

Causal Inference

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  - What if **all** countries had started to invest more in education at the same time, for different reasons?
  - The potential outcome for Country X in time 1 is different to at time 2

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  - That is why we are doing causal **inference**, not causal proof

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Causal Inference

- Which comparisons to make?
- Control units can never be perfect substitutes
- Causal Inference is all about identifying a **plausible counterfactual**
- Plausible means that **the potential outcomes of the control unit are likely to be the same as those of the treated unit**

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- If we 'treated' an outlier like the Galapagos Islands, could we find a comparable control unit?

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  - On the **Treatment Assignment Mechanism**
- If we ’treated’ an outlier like the Galapagos Islands, could we find a comparable control unit?
- Comparisons are ’better’ where the **Treatment Assignment Mechanism is independent of potential outcomes**
  - I.e. Whether you got treatment had **nothing** to do with how much you would benefit from treatment
  - This makes it more likely that potential outcomes are ’balanced’

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- And we do not know what the treatment assignment mechanism was
  - Because we did not control treatment assignment ourselves
- So we do not know which units might be appropriate counterfactuals

Causal Inference

- With complete information on potential outcomes, calculating treatment effects is trivial

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Calculating Treatment Effects

	D	Y_1	Y_0	Y_i	Real Effect, $Y_1 - Y_0$
A	1	7	?	7	?
B	0	?	5	5	?
C	0	?	4	4	?
D	1	4	?	4	?

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$$\begin{aligned} ATE = & \quad E(Y_1) - E(Y_0) & (1) \\ = & \quad 5.5 - 4.5 & (2) \\ = & \quad 1 & (3) \end{aligned}$$

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- Why?
  - The units that got treated had lower Y_1
  - The units that were controls had higher Y_0
  - The ’stand-in’ counterfactuals were wrong

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- The bias in units' potential outcomes depends on which units get treated and which ones don't
- In observational studies, we have very little protection against causal critiques
    1. Omitted variable bias (confounding)
    2. Selection bias
    3. Reverse Causation

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- These are your **potential outcomes**.

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  2. The tallest half are given an apple.

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  2. The tallest half are given an apple.
  3. You are free to choose yourself to take an apple or not.

Exercise

- Now we will consider how estimates of the average effect of fruit on happiness vary depending on how treatment (apples) are assigned.
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  4. Apples are distributed randomly

Omitted Variable Bias

- Wealthier countries are more likely to be democracies

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  - But wealthier countries are more likely to be European

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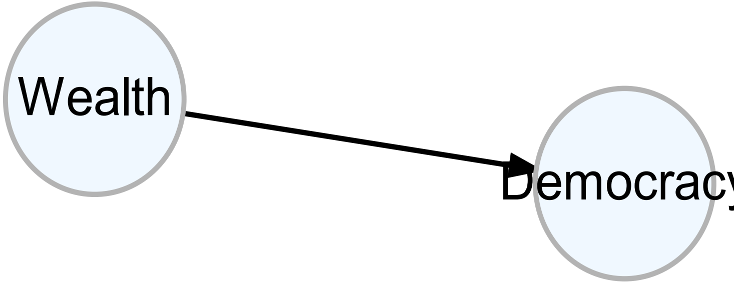
  - And democracies are more likely to be European
- Maybe the correlation just reflects the fact that European countries are 'different'?

Omitted Variable Bias



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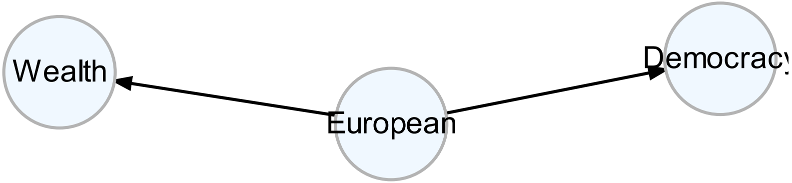

Omitted Variable Bias

- Imagine a treatment assignment mechanism where all women get treated

Treatment Assignment by Covariate

	X	D	Y_1	Y_0	Y_i	Real Effect
A	Man	0	7	4	4	3
B	Man	0	9	5	5	4
C	Woman	1	4	4	4	0
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- ATE = 4 - 4.5 = -0.5
- This is **confounding** or an **omitted variable** - another variable affects both treatment and potential outcomes

Self-Selecion Bias

- Selection Bias occurs where our data sample does not tell the complete story:

Self-Selecion Bias

- Selection Bias occurs where our data sample does not tell the complete story:
  1. **Self-selection Bias:** Units that benefit most from treatment choose to receive treatment
     - Those with the biggest difference in potential values, $Y_1 - Y_0$
  2. **Data Availability Bias:** Some types of units don't report data
     - *For reasons related to the treatment and potential outcomes*
  3. **Survival Bias:** Some types of units drop out of our sample
     - *For reasons related to the treatment and potential outcomes*

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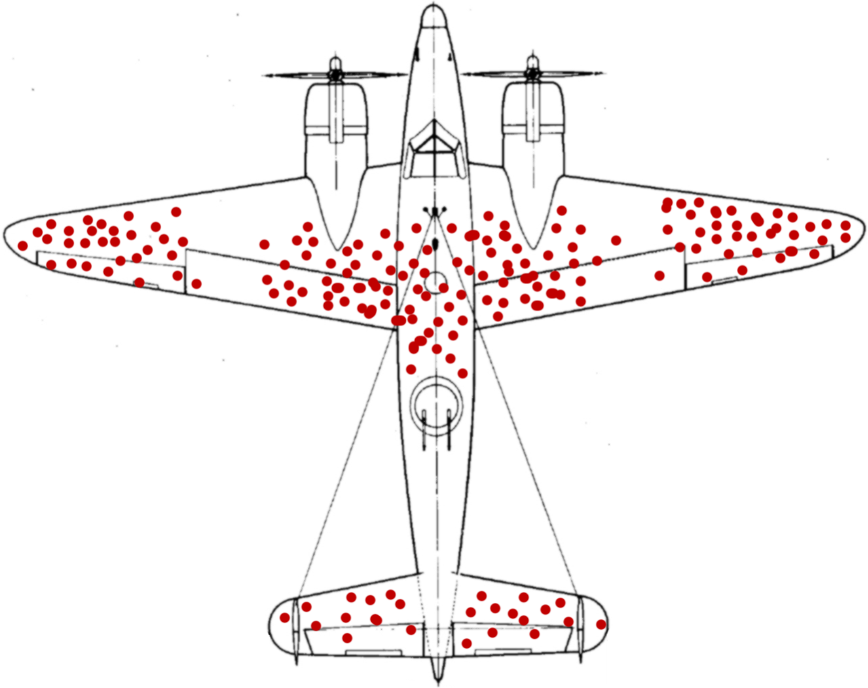
Self-Selecion Bias

- Wealthier countries are more likely to be democracies
  - But wealthy autocracies and poor democracies do not like to report data
  - So we cannot compare them
  - Only wealthy democracies 'select' into our sample



Self-Selection Bias

- Imagine a treatment assignment mechanism where people get to *choose* their treatment

Treatment Assignment by Self-Selection

	D	Y_1	Y_0	Y_i	Real Effect
A	1	7	4	7	3
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A	1	7	4	7	3
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D	0	4	3	3	1
$E(Y_1) =$		8			
$E(Y_0) =$			3.5		

Self-Selection Bias

- Imagine a treatment assignment mechanism where people get to *choose* their treatment

Treatment Assignment by Self-Selection

	D	Y_1	Y_0	Y_i	Real Effect
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D	0	4	3	3	1
$E(Y_1) =$		8			
$E(Y_0) =$			3.5		

- ATE = 8 - 3.5 = 4.5
- This is **self-selection bias** - those with a big jump in potential outcomes ($Y1 - Y0$) choose treatment

Problems with Observational Data

- We can identify the source of these biases in potential outcomes:

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$$\underbrace{E(Y_i|D=1)-E(Y_i|D=0)}_{\text{Observed Effect}}=\underbrace{E(Y_{1i}-Y_{0i})}_{\text{Real ATE}}$$
$$+\underbrace{\frac{1}{2}\Big[E(Y_{1i}|D=1)-E(Y_{1i}|D=0)\Big]}_{\text{Imbalance on } Y_1}+\underbrace{\frac{1}{2}\Big[E(Y_{0i}|D=1)-E(Y_{0i}|D=0)\Big]}_{\text{Imbalance on } Y_0} \tag{5}$$

NB: For equal-sized treatment and control groups

Problems with Observational Data

- Disaggregating the Self-Selection Bias:

$$\frac{(7+9-4-3)}{2} = \frac{(7+9+4+4-4-5-4-3)}{4} + \frac{1}{2}\left[\frac{(7+9)}{2} - \frac{(4+4)}{2}\right] + \frac{1}{2}\left[\frac{(4+5)}{2} - \frac{(4+3)}{2}\right]$$

$$4.5 = {\color{red}2} + 2 + \frac{1}{2} \tag{6}$$

Problems with Observational Data

- Depending on the treatment assignment mechanism we get a range of Average Treatment Effects:

Comparing Average Treatment Effects

Treated Units	**ATE**
Real Effect for all units	2
Units A & D	1
Women (Omitted Variable Bias)	-0.5
Biggest gains (Self-selection)	4.5

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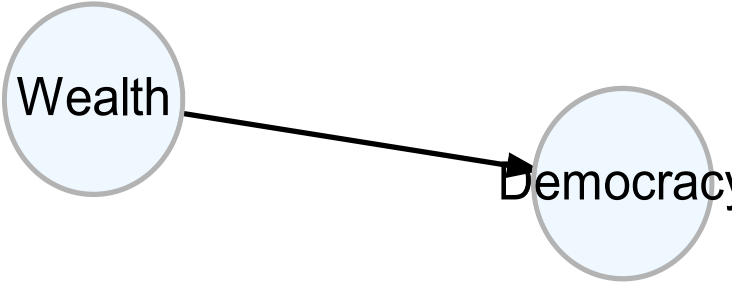
- Both may be true

Reverse Causation



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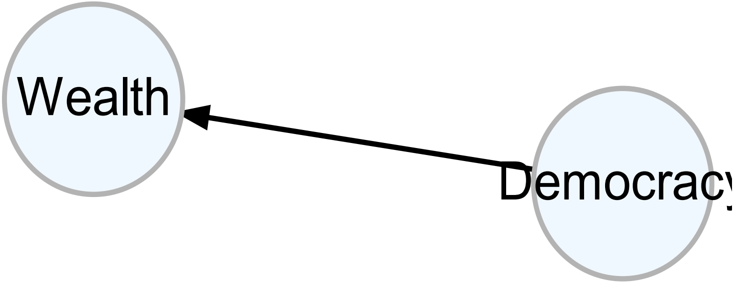

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- Assume treatment has *no* effect

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- ATE = 4 - 4 = 0. There is no effect.
- The (negative) correlation between *D* and *Y* is because *Y* **causes** *D*

Causal Inference

Types of Research Design:

	Researcher controls the treatment assignment	Treatment assignment mechanism likely to create comparable potential outcomes ('Conditional Independence')
Controlled Experiments	Yes	Yes
Natural Experiments	No	Yes
Observable Studies	No	No

Problems with Observational Data

- Observational Studies

Problems with Observational Data

- Observational Studies
  - Household surveys
  - Simple regression on secondary data
  - Interviews of a random sample