Interpreting and Critiquing Causal Evidence

Day 2 - Fundamental Critiques

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Section 1

Introduction

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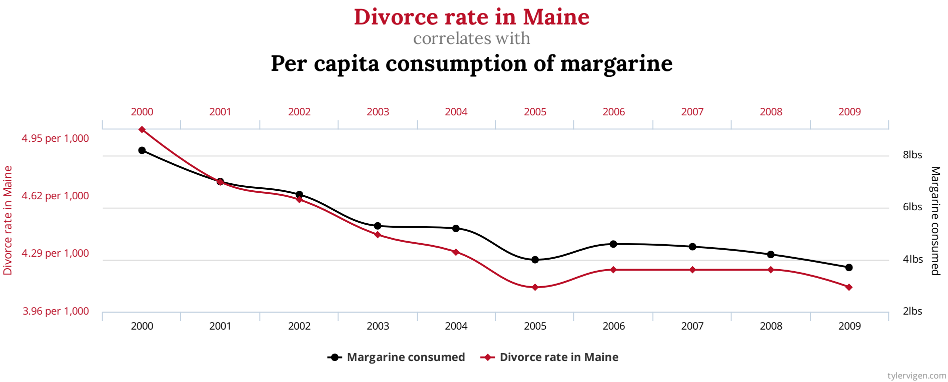
- *More* data will not help
- The problem is the *type* of data; it does not allow us to answer the causal question



Divorce rate in Maine
correlates with
Per capita consumption of margarine
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
4.95 per 1,000
4.62 per 1,000
4.29 per 1,000
3.96 per 1,000
Divorce rate in Maine
8lbs
6lbs
4lbs
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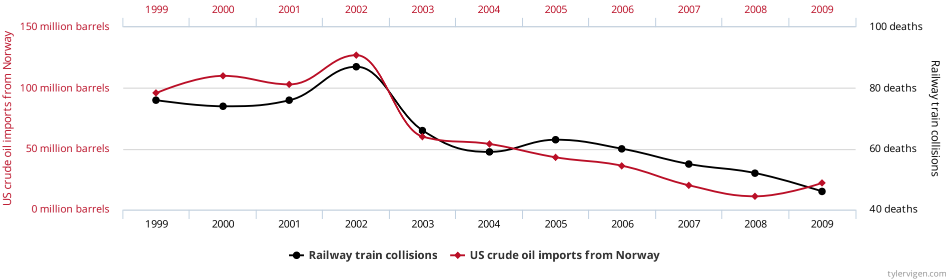
Margarine consumed
Margarine consumed
Divorce rate in Maine
tylervigen.com

US crude oil imports from Norway

correlates with

Drivers killed in collision with railway train



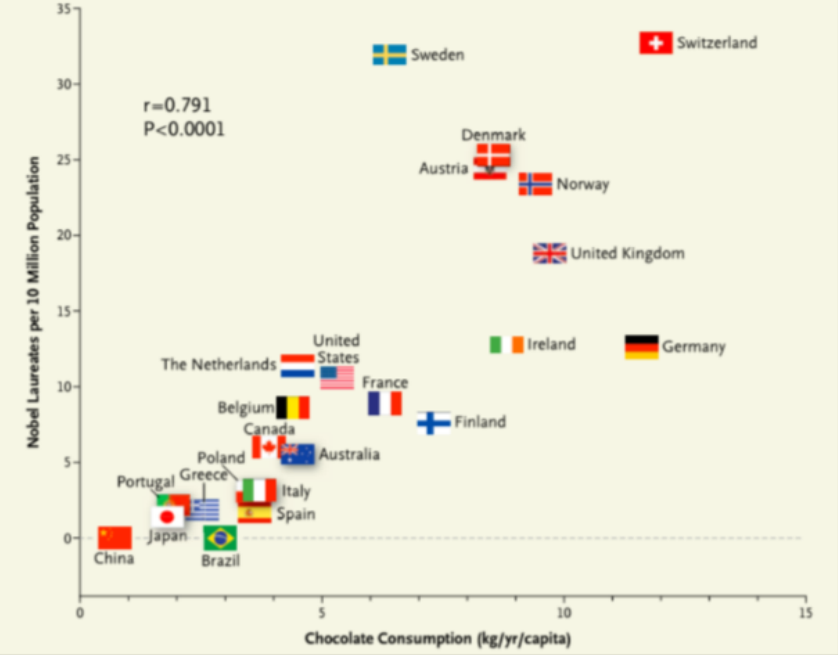


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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  - For **explanation**, correlation also fails - it is no *explanation* to say that Switzerland has the most Nobel Laureates because it has the highest chocolate consumption

Section 2

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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    - If we study 20 outcomes, on average one will show a significant effect even with no real causal effect

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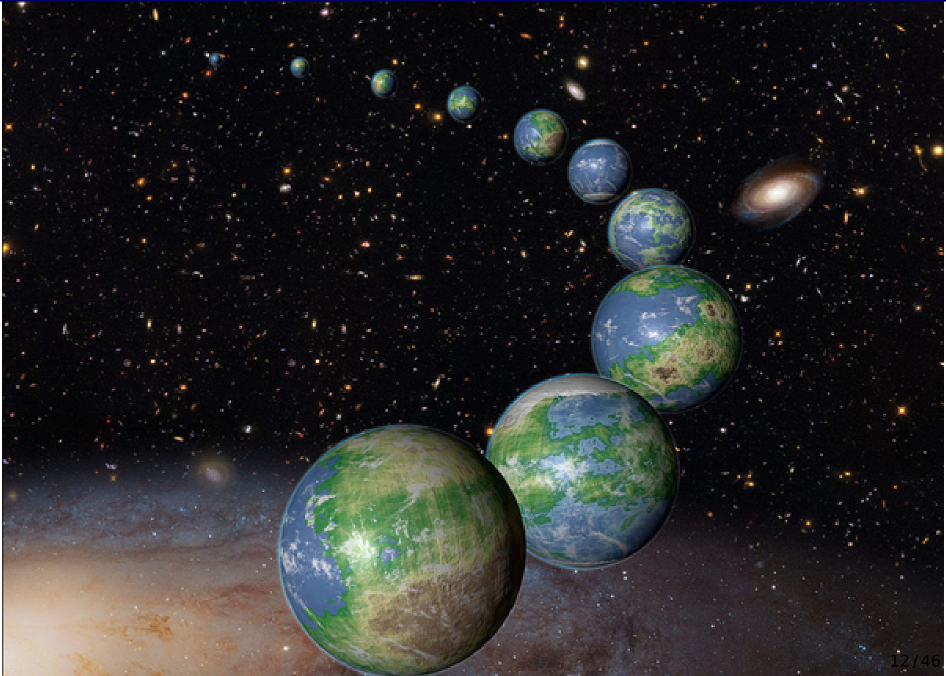

Causal Inference

Potential Outcomes are just another Variable for each Unit

	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
	Y_1	Y_0	$Y_1 - Y_0$
Brasil	6	3	3
Argentina	8	5	3
Uruguay	3	3	0
Bolivia	0	2	-2
Colombia	4	4	0
Peru	4	2	2

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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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Average Treatment Effect	**4.17**	**3.17**	**1**

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

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Potential Outcomes Example

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
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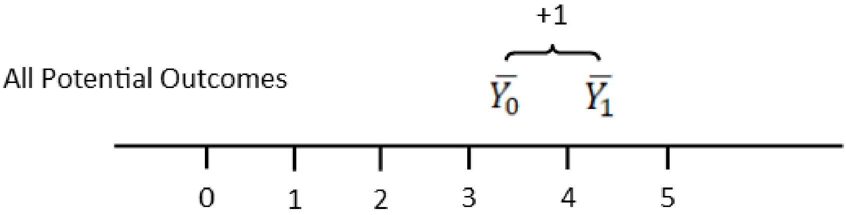

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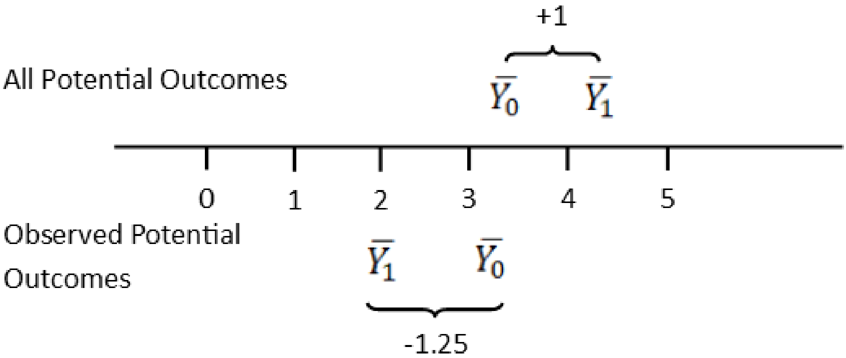

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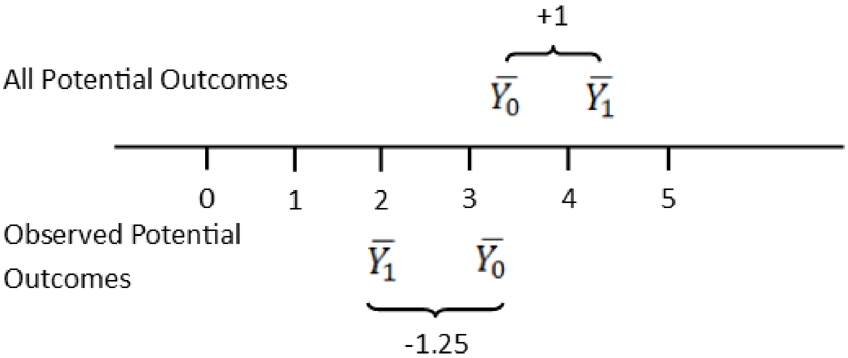

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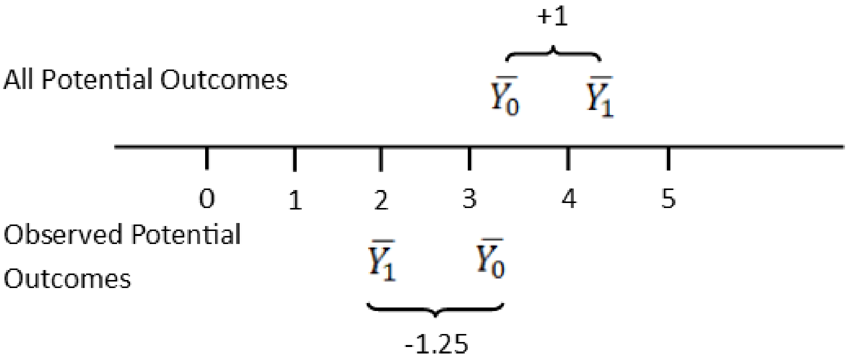

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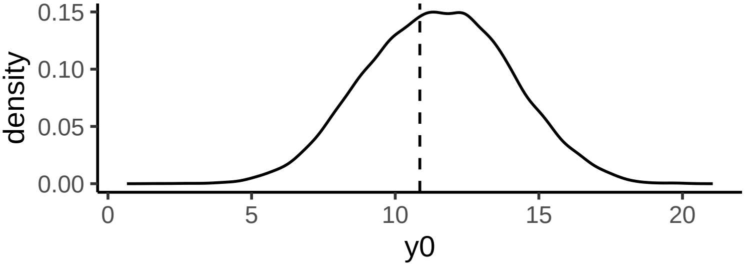

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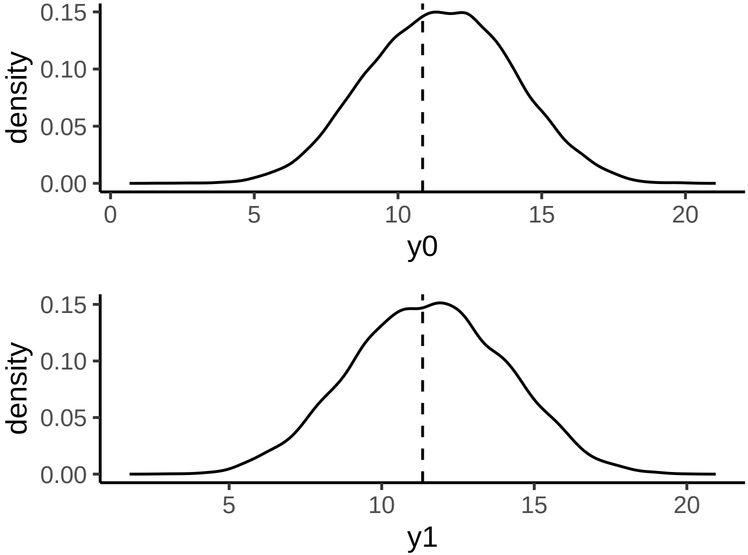

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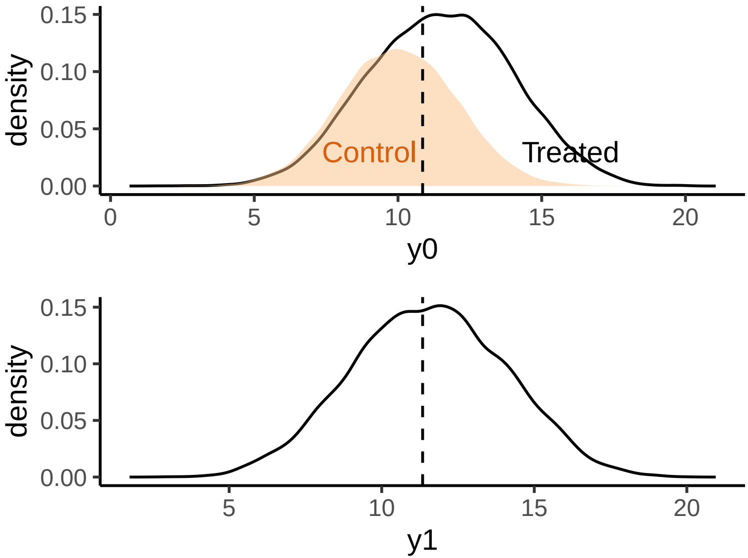

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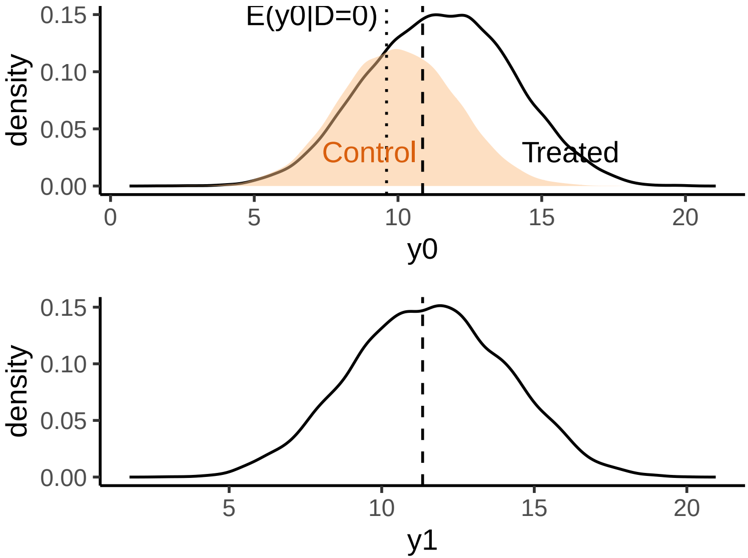

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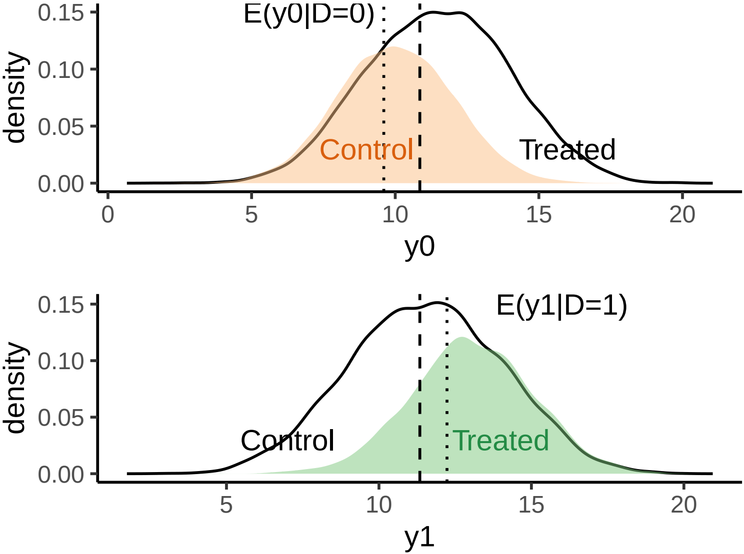

Section 3

Treatment Assignment

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- 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 the treatment affects you
  - This makes it more likely that potential outcomes are 'balanced'/'representative'

Treatment Assignment Mechanism

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- So we do not know which units might be appropriate counterfactuals

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- $E(Y|D=1) = E(Y|D=0) = E(Y)$

Section 4

3 Critiques

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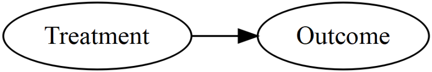
- So basic regression is **biased**

Omitted Variable Bias

A real causal relationship:



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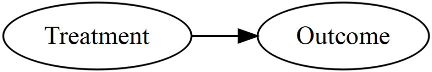

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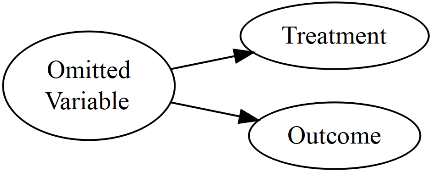

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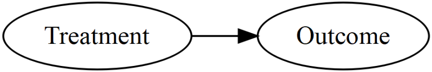

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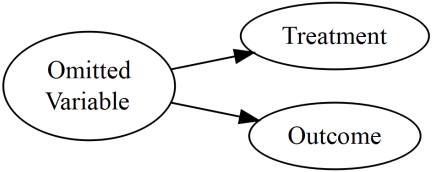
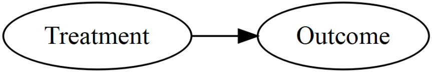


- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

Omitted Variable Bias

A real causal relationship:



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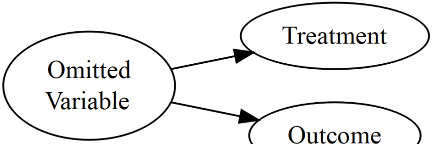

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1

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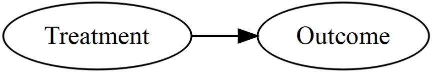

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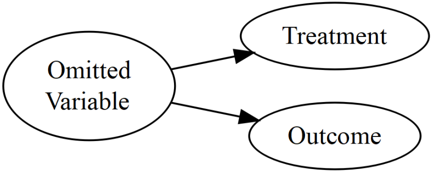

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

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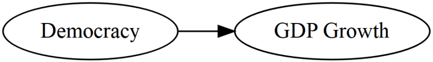

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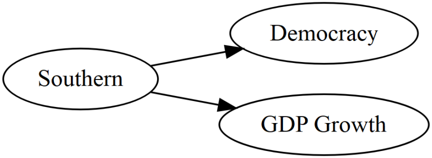

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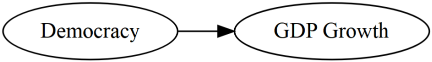

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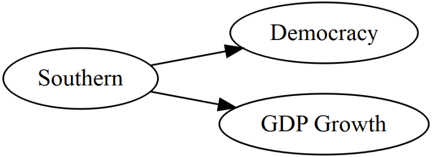
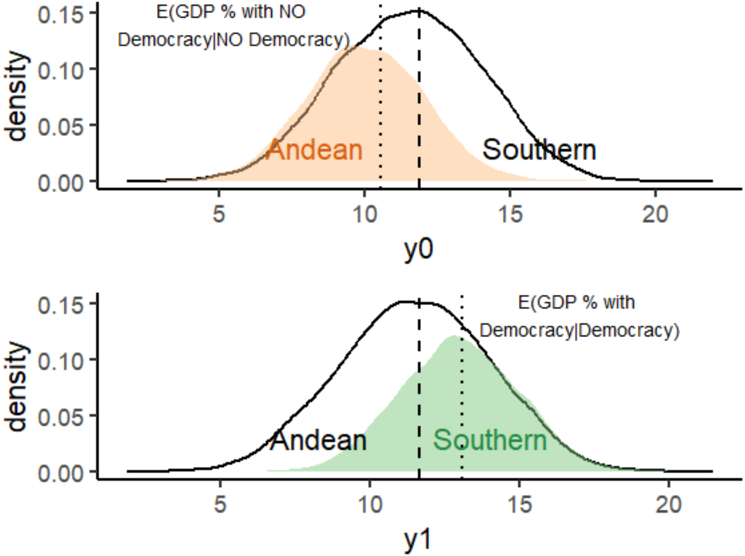


- Southern Cone countries faced conditions that encouraged both democracy and rapid GDP growth

Omitted Variable Bias



Omitted Variable Bias

	Andean?	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Treatment Effect**
	X_i	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	1	6	?	?
Argentina	1	1	8	?	?
Uruguay	1	1	3	?	?
Bolivia	0	0	?	2	?
Colombia	0	0	?	4	?
Peru	0	0	?	2	?
Average Treatment Effect			**5.7**	**2.7**	**3**

Omitted Variable Bias

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

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

Omitted Variable Bias

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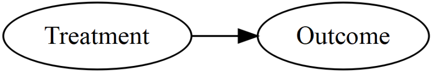
$$\hat{ATE} = E(Y_1|D=1) - E(Y_0|D=0)$$

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

Reverse Causation

A real causal relationship:



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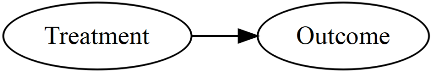

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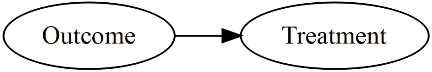

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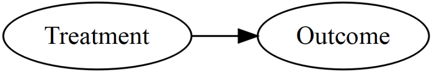

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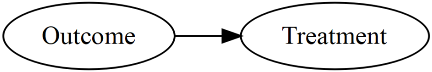

- D does not affect Y, but higher Y makes treatment (D) more likely

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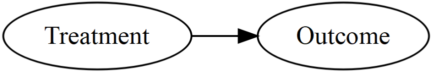

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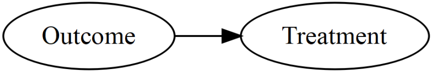

- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are **correlated**

Reverse Causation

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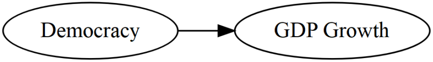

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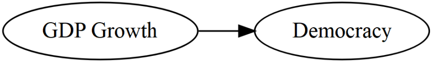

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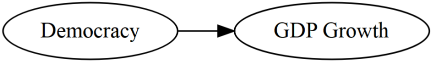

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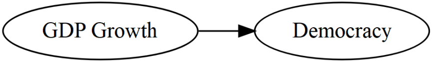

- GDP Growth encourages democratization

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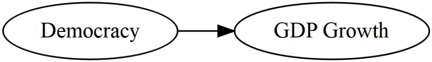

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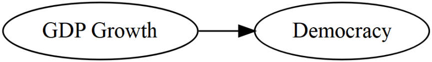


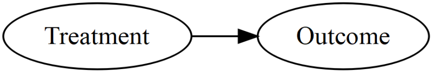
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Causal Inference

	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	1	4	?	?
Peru	0	?	2	?
Average Treatment Effect		**6**	**2.3**	**3.7**

Selection Bias

A real causal relationship:



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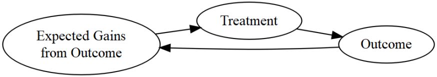

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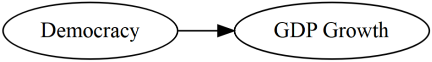

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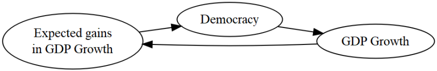

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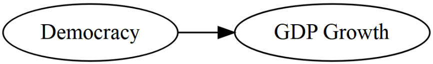

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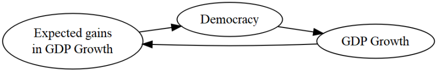

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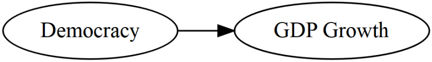

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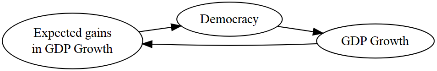

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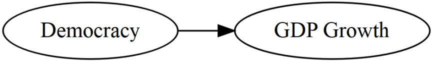

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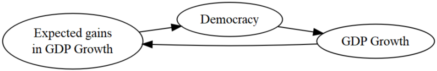

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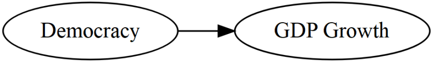

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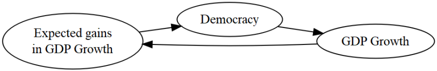

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- We don't see any of the low y_1's of units which avoid treatment
    - Countries which can boost their GDP growth by becoming a democracy choose to democratize
    - Ex. Mexico? Poland?

Self-Selection Bias

	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	0	?	4	?
Peru	1	4	?	?
Average Treatment Effect		**6**	**3**	**3**

Self-Selecion Bias

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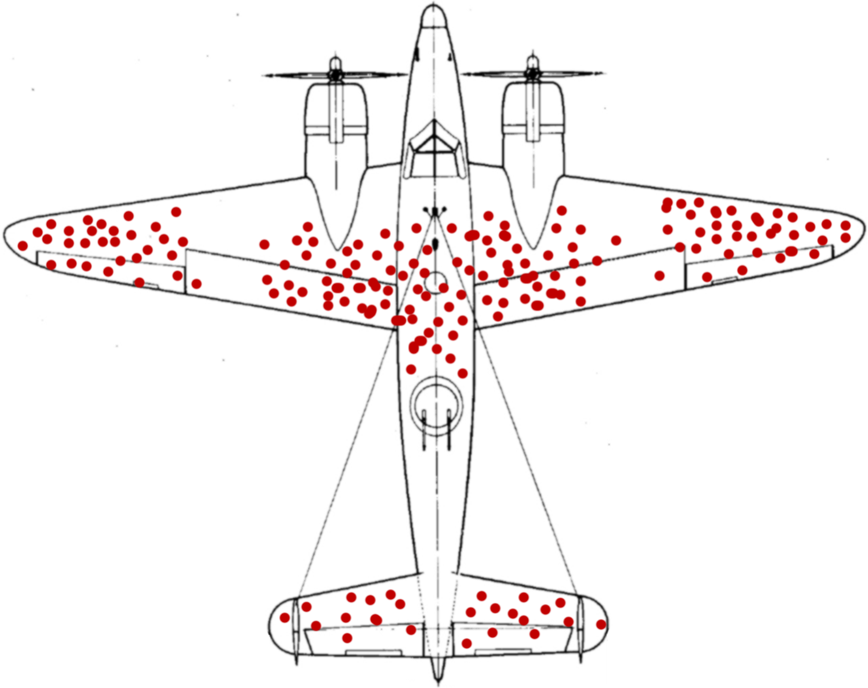
     - Eg. Wealthy autocracies and poor democracies do not like to report data
     - Only wealthy democracies 'select' into our sample
  3. **Survival Bias:** Some types of units drop out of our sample
     - *For reasons related to the treatment and potential outcomes*



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	1
Bolivia and Colombia treated	-1.25
Omitted Variable Bias (Southern Cone)	3
Reverse Causation	3.7
Self-selection (Biggest GDP gains)	3

3 Critiques

- *ANY* time you see a paper based on observational data, you should try to make the three critiques:

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- *ANY* time you see a paper based on observational data, you should try to make the three critiques:
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- In all these cases, treatment assignment is not independent of potential outcomes