Making Causal Critiques

Day 2 - Fundamental Critiques

Jonathan Phillips

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Section 1

Introduction

What do political scientists **know**?

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- Proportional Representation electoral systems have more parties
- Democracies do not go to war with each other
- Development helps democracies endure
- ...And that's about it

What do political scientists **know**?

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  - Many add **descriptive** knowledge
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  - Many highlight **correlations** between variables

Learning from Data

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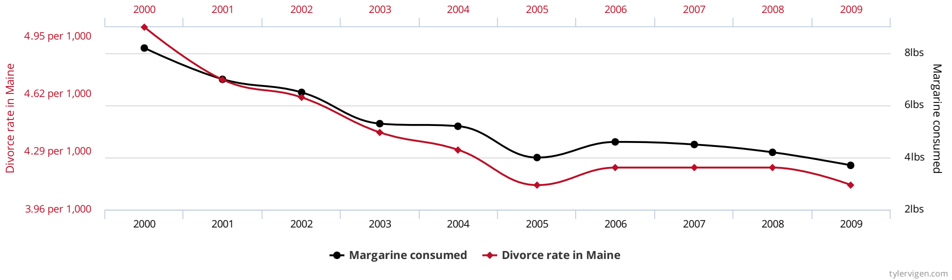
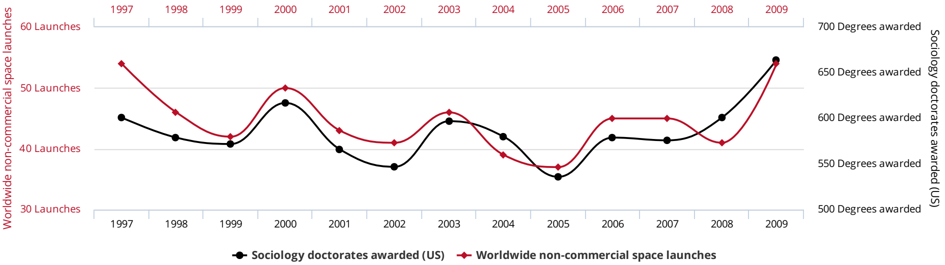
- *More* data will not help
- The problem is the *type* of data; it does not allow us to answer the causal question

Divorce rate in Maine
correlates with
Per capita consumption of margarine



Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)



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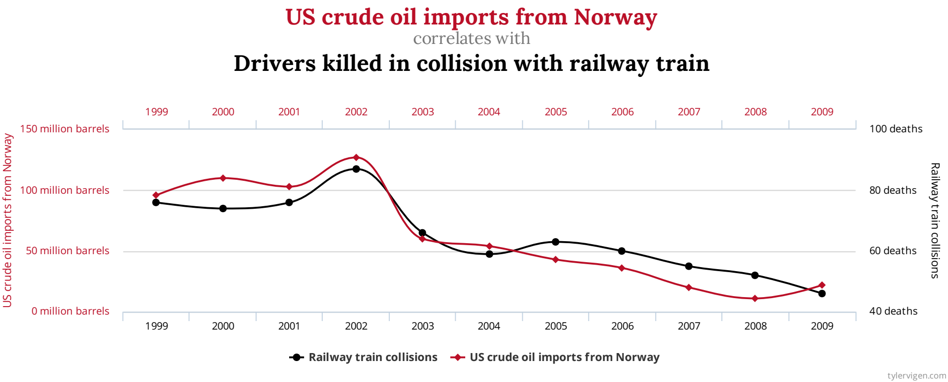
US crude oil imports from Norway
correlates with
Drivers killed in collision with railway train
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
150 million barrels
100 million barrels
50 million barrels
0 million barrels
US crude oil imports from Norway
100 deaths
80 deaths
60 deaths
40 deaths
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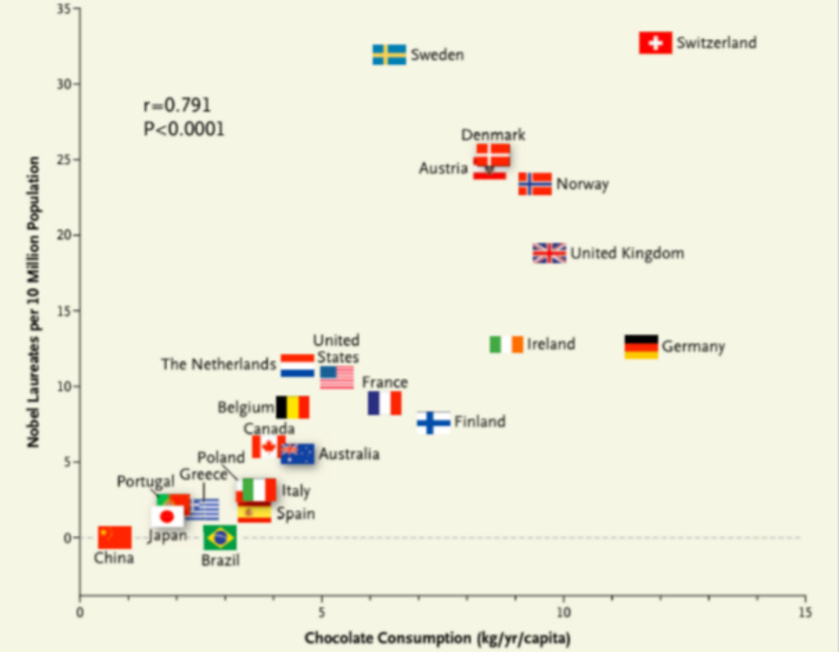

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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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

Section 2

Causal Inference

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- A focus on a single explanatory variable D requires us to clearly define this 'treatment'
- AND to clearly define a control
  - What is the opposite of investing \$1bn in education?
  - No investment, or investing it elsewhere?
- Define treatment:

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

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  - Is that outcome the end of the causal chain?
  - 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

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$$Y_{Di} = \begin{cases} Y_{1i} \text{ GDP Growth of Brazil in 2010 if a Democracy} \\ Y_{0i} \text{ GDP Growth of Brazil in 2010 if NOT a Democracy} \end{cases}$$

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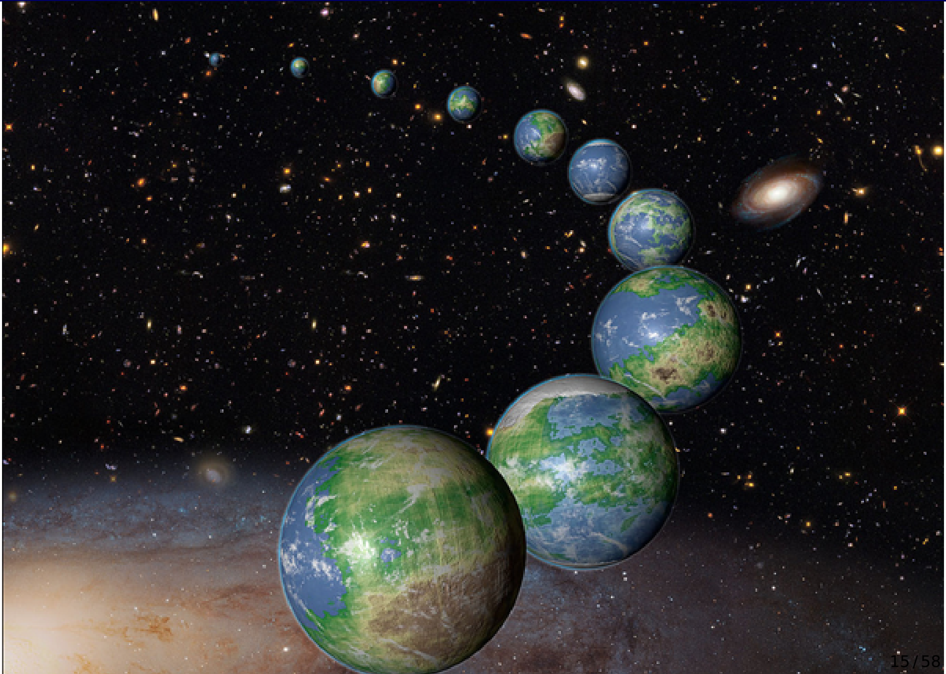

Causal Inference

Potential Outcomes are just another Variable 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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$$Y_i^{obs} = D_i \cdot Y_{1i} + (1 - D_i) \cdot Y_{0i}$$

Causal Inference

Potential Outcomes Example

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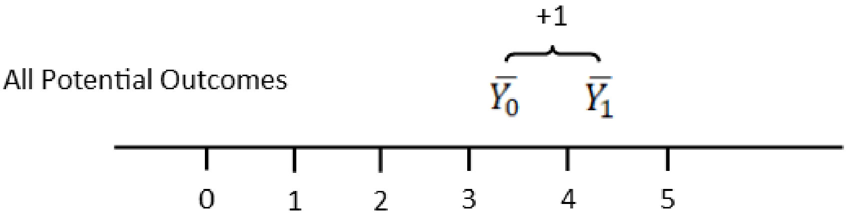

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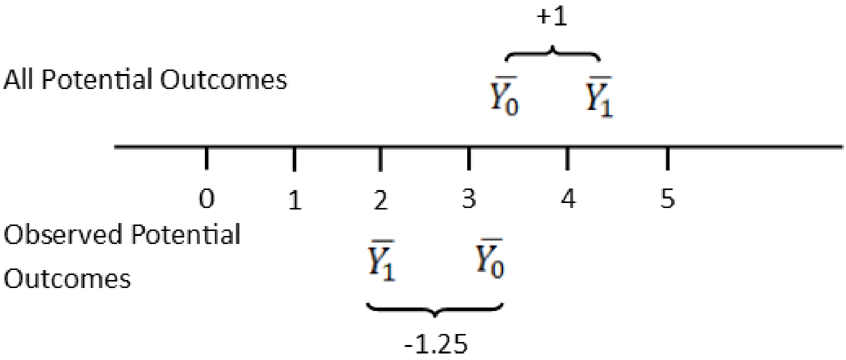

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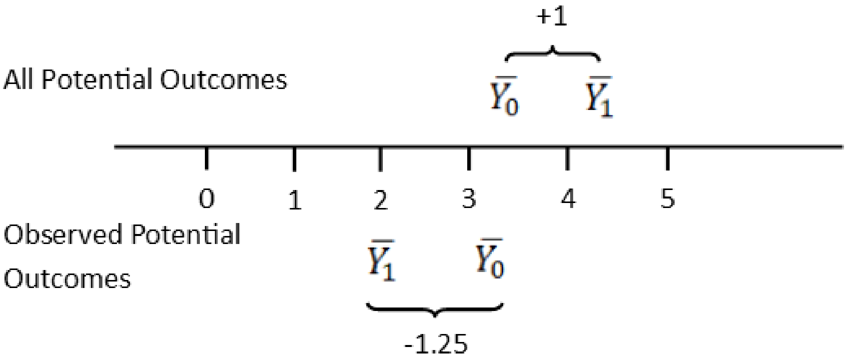

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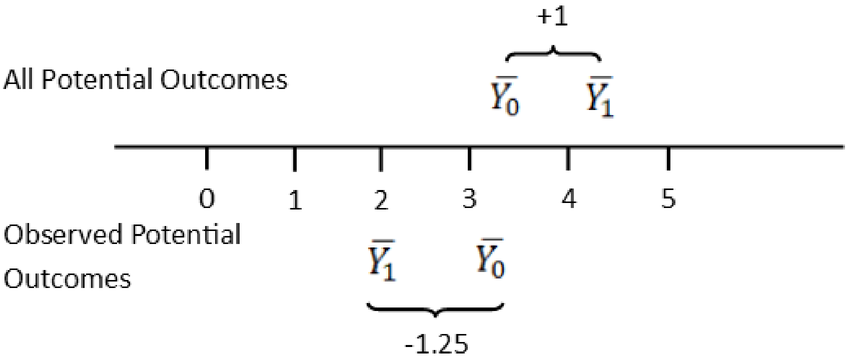

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  - Causal effects are **biased**

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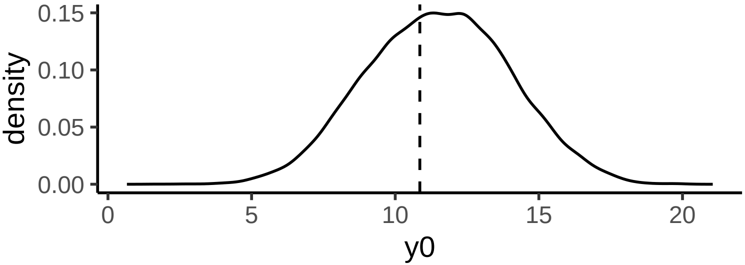

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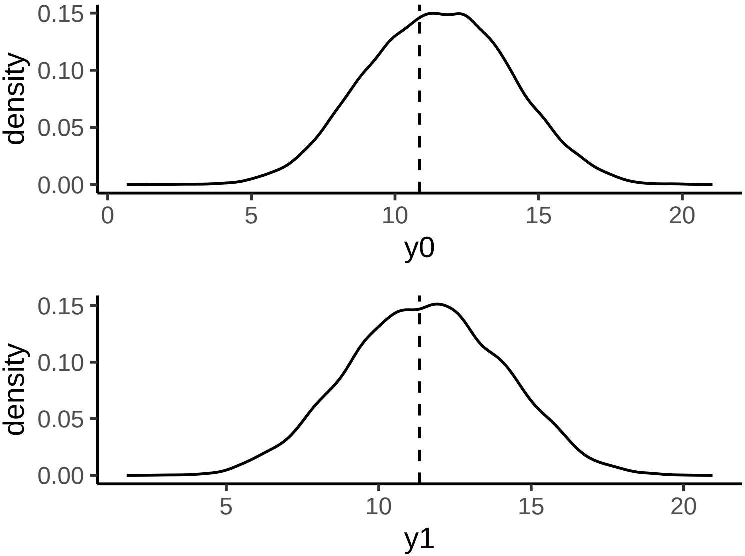

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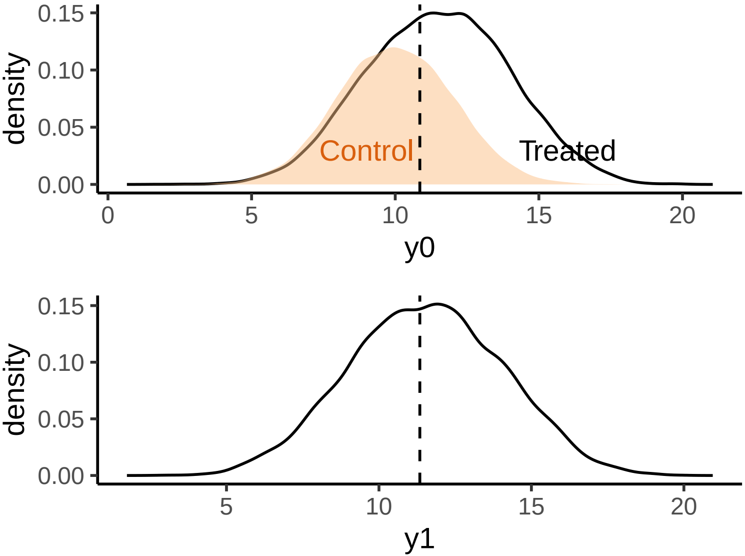

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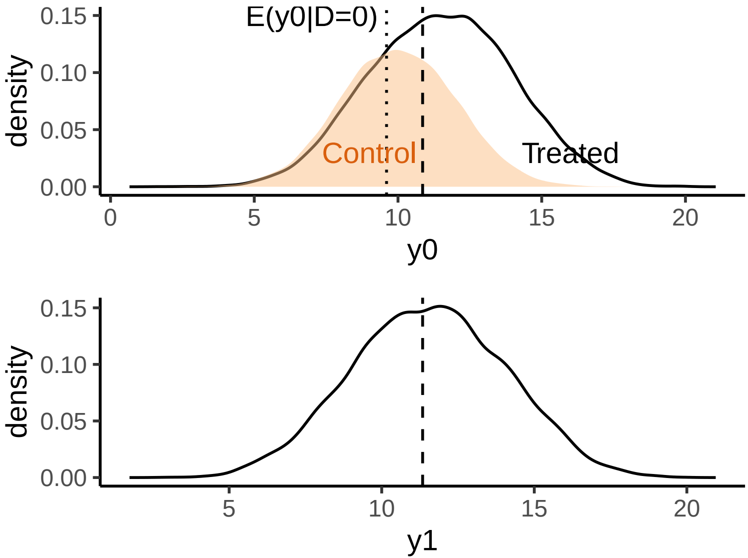

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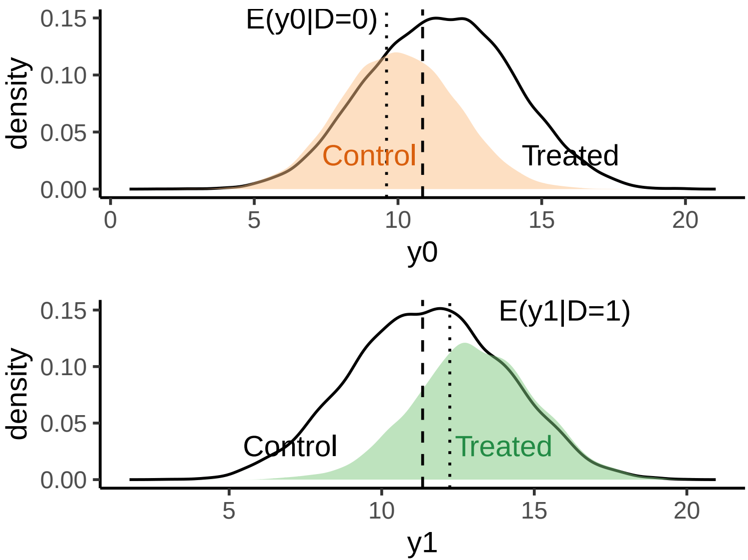

Causal Inference

- Lots of averages:

		Hypothetical outcome	
		$Y0$	$Y1$
Actual Treatment	$D = 0$	$E(Y_{0i}\|D = 0)$	$E(Y_{1i}\|D = 0)$
	$D = 1$	$E(Y_{0i}\|D = 1)$	$E(Y_{1i}\|D = 1)$

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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 you would benefit from treatment
  - This makes it more likely that potential outcomes are 'balanced'

Treatment Assignment Mechanism

- A ’real-world’ treatment assignment is *highly unlikely* to create comparable potential outcomes

Treatment Assignment Mechanism

- A 'real-world' treatment assignment is *highly unlikely* to create comparable potential outcomes
- And we do not know what the treatment assignment mechanism was
  - Because we did not control treatment assignment ourselves

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

Exercise

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- These are your **potential outcomes**.

Exercise

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  1. All the female participants are given an apple.
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  3. You are free to choose yourself to take an apple or not.
  4. Apples are distributed randomly

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Treatment Assignment does NOT depend on the values of units’ Potential Outcomes

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$(Y_1, Y_0) \perp D$

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Treatment Assignment does NOT depend on the values of units’ Potential Outcomes

$(Y_1, Y_0) \perp D$

$Pr(D|(Y_1, Y_0)) = Pr(D)$

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

Section 4

3 Critiques

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- Why are potential outcomes biased in our data?

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  1. Omitted Variables

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    2. Reverse Causation

3 Critiques

- Why are potential outcomes biased in our data?
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  3. Selection Bias

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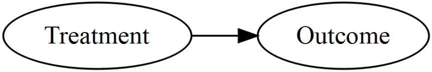
3 Critiques

- 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**

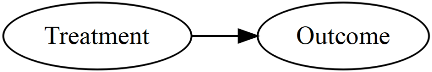
Omitted Variable Bias

A real causal relationship:

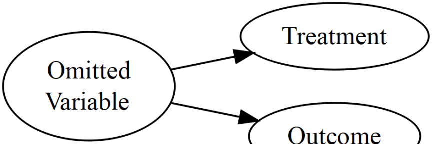


Omitted Variable Bias

A real causal relationship:



Being misled by omitted variable bias:



Omitted Variable Bias

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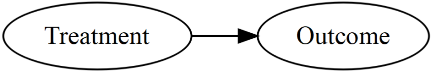

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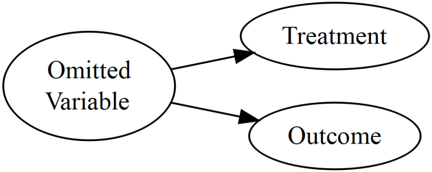
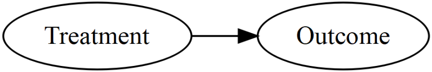


- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

Omitted Variable Bias

A real causal relationship:



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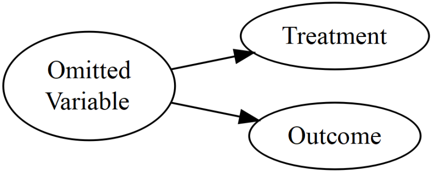

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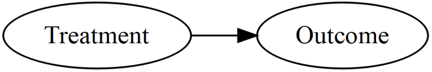

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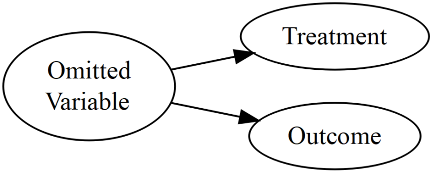

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

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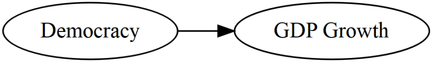

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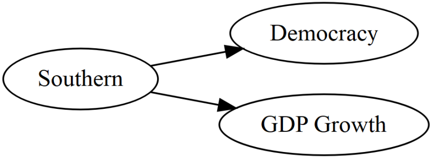

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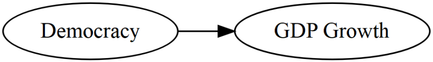

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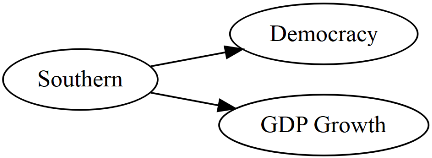
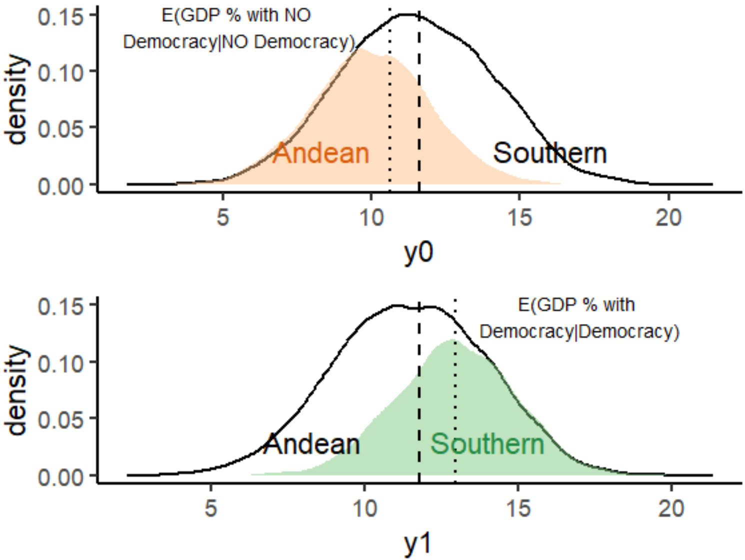


- Southern Cone countries faced conditions that encouraged both democracy and rapid GDP growth

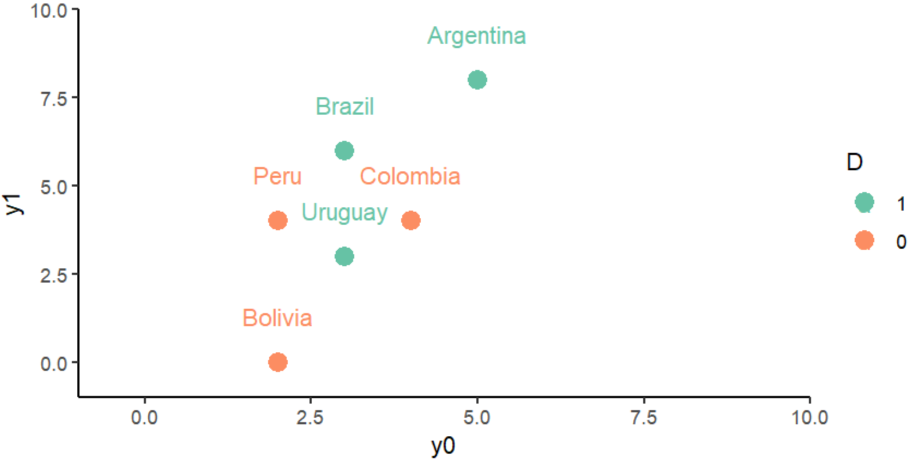
Omitted Variable Bias



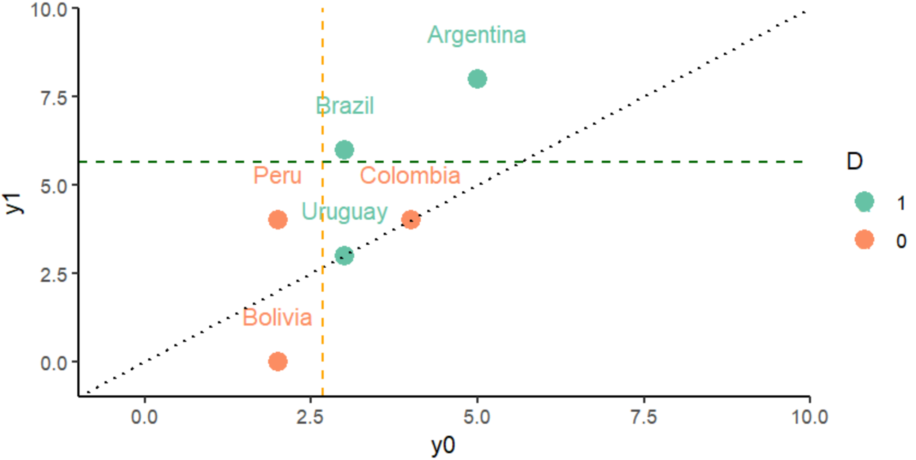
Omitted Variable Bias

	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



Omitted Variable Bias



- $E(Y_1|D=1) - E(Y_0|D=0) = 5.7 - 2.7 = 3$

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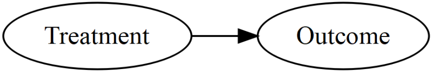
$$A\hat{T}E = E(Y_1|D=1) - E(Y_0|D=0)$$

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

Reverse Causation

A real causal relationship:



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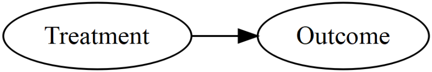

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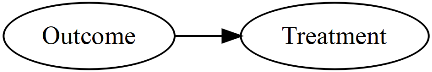

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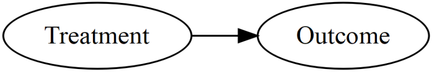

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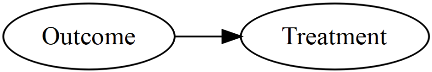

- *D* does not affect *Y*, but higher *Y* makes treatment (*D*) more likely

Reverse Causation

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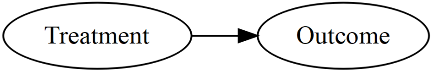

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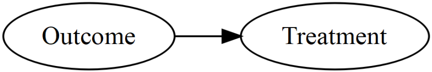
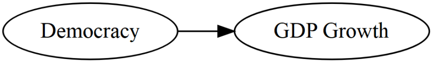


- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are **correlated**

Reverse Causation

A real causal relationship:



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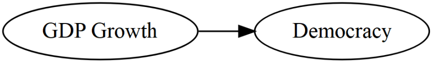
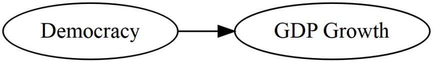


Reverse Causation

A real causal relationship:



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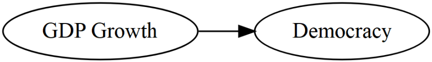

- GDP Growth encourages democratization

Reverse Causation

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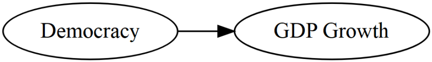

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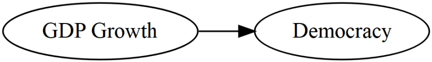
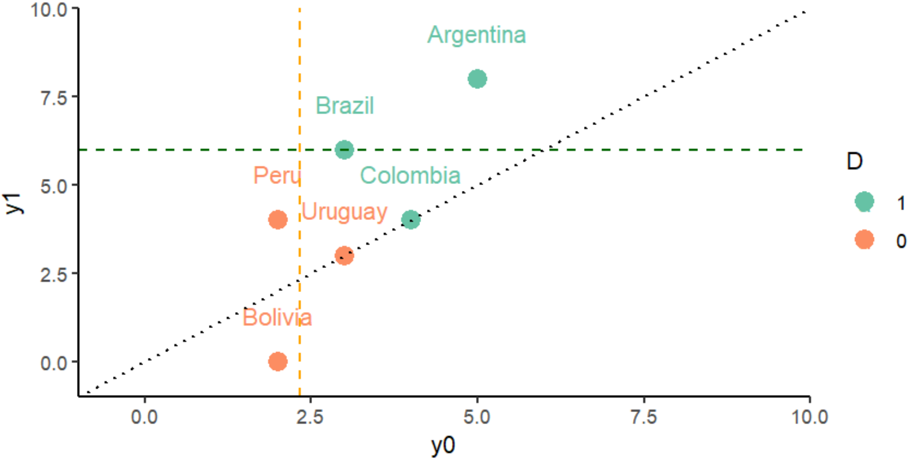


- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation



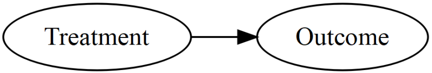
- $E(Y_1|D=1) - E(Y_0|D=0) = 6 - 2.3 = 3.7$

Causal Inference

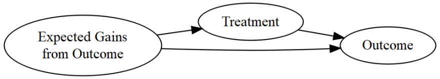
	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	1	4	?	?
Peru	0	?	2	?
Average Treatment Effect		**6**	**2.3**	**3.7**

Selection Bias

A real causal relationship:



Being misled by Selection Bias:



Selection Bias

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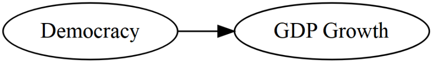

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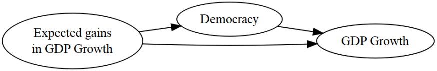
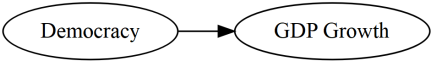


Selection Bias

A real causal relationship:



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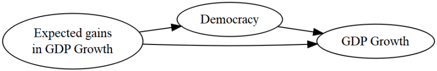
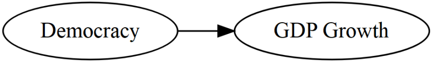


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

A real causal relationship:



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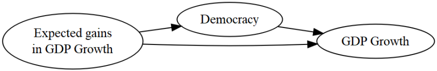
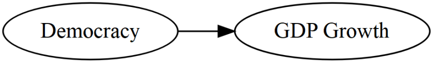


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Selection Bias

A real causal relationship:



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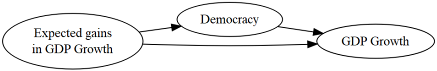

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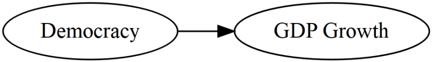
  - Countries which can boost their GDP growth by becoming a democracy choose to democratize

Selection Bias

A real causal relationship:



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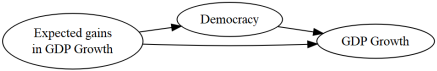
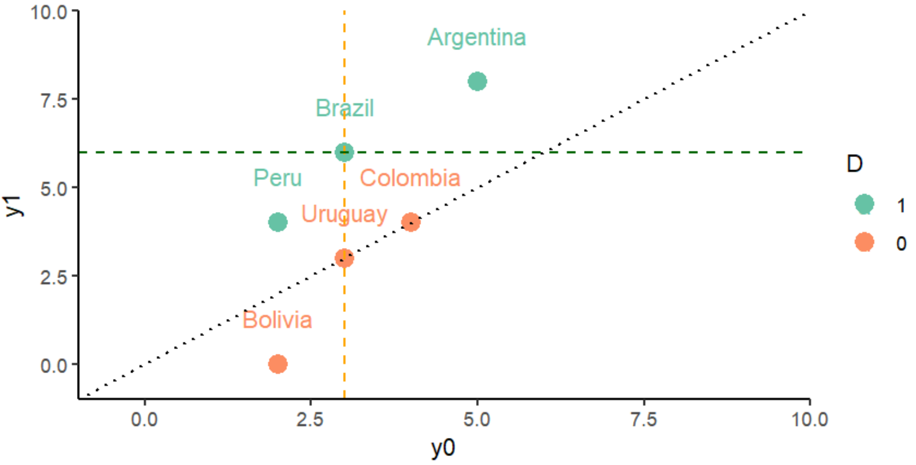


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment
  - Countries which can boost their GDP growth by becoming a democracy choose to democratize
  - Ex. Mexico? Myanmar?

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-Selection Bias



- $E(y_1|D=1) - E(y_0|D=0) = 6 - 3 = 3$

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 $Y_{1i} = Y_{0i} + \alpha_i$

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

NB: For equal-sized treatment and control groups

Self-Selection Bias

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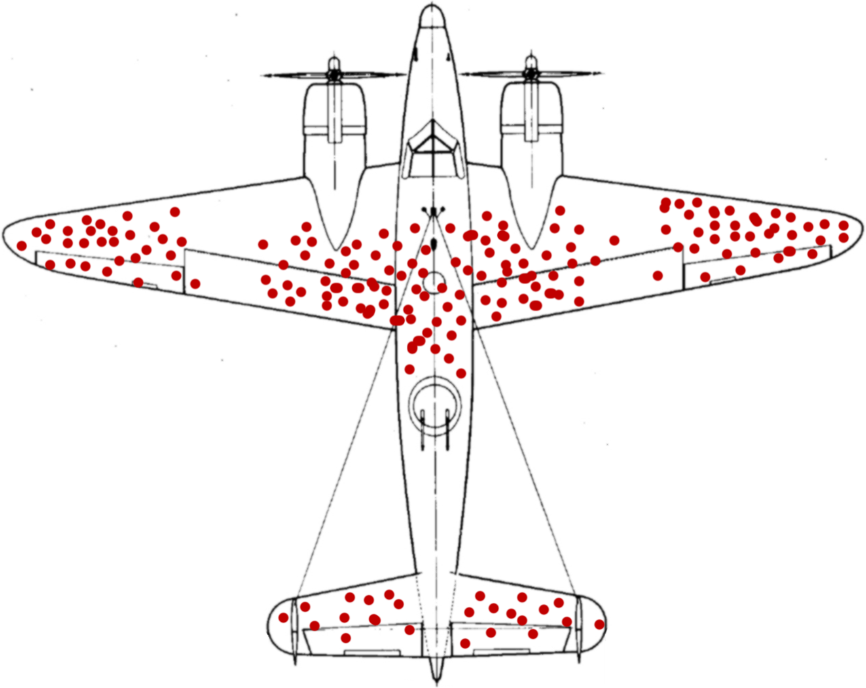
     - Only wealthy democracies 'select' into our sample
  3. **Survival Bias:** Some types of units drop out of our sample
     - *For reasons related to the treatment and potential outcomes*



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

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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
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    3. Selection Bias
- In all these cases, treatment assignment is not independent of potential outcomes