Making Causal Critiques

Day 2 - Fundamental Critiques

Jonathan Phillips

January 26, 2020

Section 1

Introduction

What do political scientists **know**?

- Door-to-door political campaigning works

What do political scientists **know**?

- Door-to-door political campaigning works
- Proportional Representation electoral systems have more parties

What do political scientists **know**?

- Door-to-door political campaigning works
- Proportional Representation electoral systems have more parties
- Democracies do not go to war with each other

What do political scientists **know**?

- Door-to-door political campaigning works
- Proportional Representation electoral systems have more parties
- Democracies do not go to war with each other
- Development helps democracies endure

What do political scientists **know**?

- Door-to-door political campaigning works
- 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**?

- Thousands of books and papers have *not* generated much knowledge about what explains political outcomes

What do political scientists **know**?

- Thousands of books and papers have *not* generated much knowledge about what explains political outcomes
  - Many add **descriptive** knowledge

What do political scientists **know**?

- Thousands of books and papers have *not* generated much knowledge about what explains political outcomes
  - Many add **descriptive** knowledge
  - Many investigate **specific** events, not generalizable variables

What do political scientists **know**?

- Thousands of books and papers have *not* generated much knowledge about what explains political outcomes
  - Many add **descriptive** knowledge
  - Many investigate **specific** events, not generalizable variables
  - Many highlight **correlations** between variables

Learning from Data

- Why aren’t case studies enough?

Learning from Data

- Why aren’t case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*
- The problem is that there are many variables that *could* explain success

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*
- The problem is that there are many variables that *could* explain success
- And detailed case studies can help us identify plausible *hypotheses*

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*
- The problem is that there are many variables that *could* explain success
- And detailed case studies can help us identify plausible *hypotheses*
- But the only way to *confirm* the hypothesis is to verify that:

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*
- The problem is that there are many variables that *could* explain success
- And detailed case studies can help us identify plausible *hypotheses*
- 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)

Learning from Data

- Why aren't case studies enough?
  - If we want to know why some countries are more successful democracies than others, surely we have to examine the successful countries in detail?
  - Yes! But that's not *sufficient*
- The problem is that there are many variables that *could* explain success
- And detailed case studies can help us identify plausible *hypotheses*
- 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)

Learning from Data

- For example, we could look at India and conclude large Asian countries produce successful democracies

Learning from Data

- For example, we could look at India and conclude large Asian countries produce successful democracies
  - But...China

Learning from Data

- For example, we could look at India and conclude large Asian countries produce successful democracies
  - But...China
  - 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

Learning from Data

- Even when we compare multiple cases:

Learning from Data

- Even when we compare multiple cases:
- **Correlation is not causation**

Learning from Data

- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations

Learning from Data

- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...

Learning from Data

- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...

Learning from Data

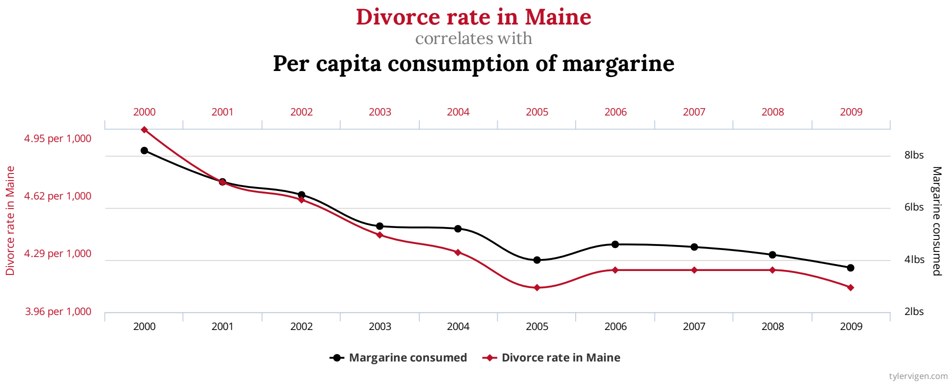
- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...
  - But we cannot conclude that there is a causal effect of D on Y

Learning from Data

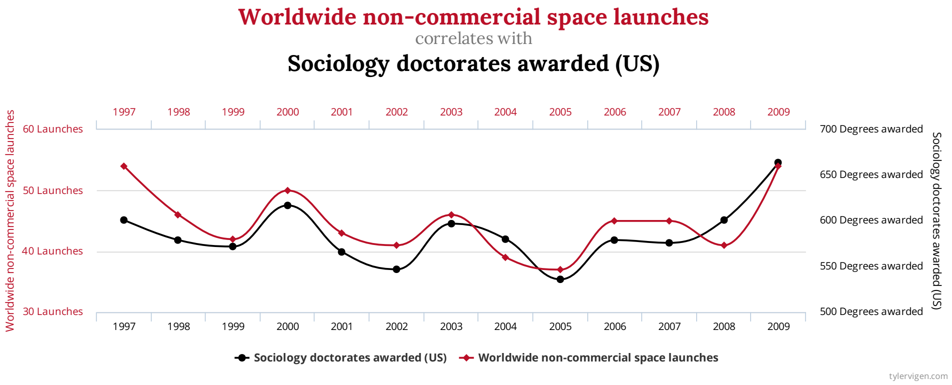
- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...
  - But we cannot conclude that there is a causal effect of D on Y
- *More* data will not help

Learning from Data

- Even when we compare multiple cases:
- **Correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...
  - But we cannot conclude that there is a causal effect of D on Y
- *More* data will not help
- The problem is the *type* of data; it does not allow us to answer the causal question



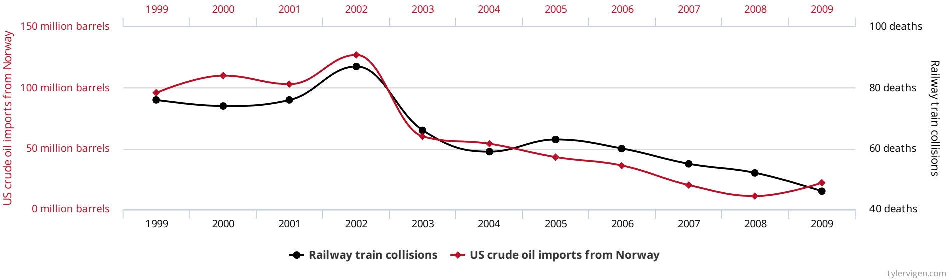
Divorce rate in Maine
correlates with
Per capita consumption of margarine
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
4.95 per 1,000
4.62 per 1,000
4.29 per 1,000
3.96 per 1,000
Divorce rate in Maine
8lbs
6lbs
4lbs
2lbs
Margarine consumed
Margarine consumed
Divorce rate in Maine
tylervigen.com


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
30 Launches
Worldwide non-commercial space launches
700 Degrees awarded
650 Degrees awarded
600 Degrees awarded
550 Degrees awarded
500 Degrees awarded
Sociology doctorates awarded (US)
Sociology doctorates awarded (US)
Worldwide non-commercial space launches
tylervigen.com

US crude oil imports from Norway

correlates with

Drivers killed in collision with railway train



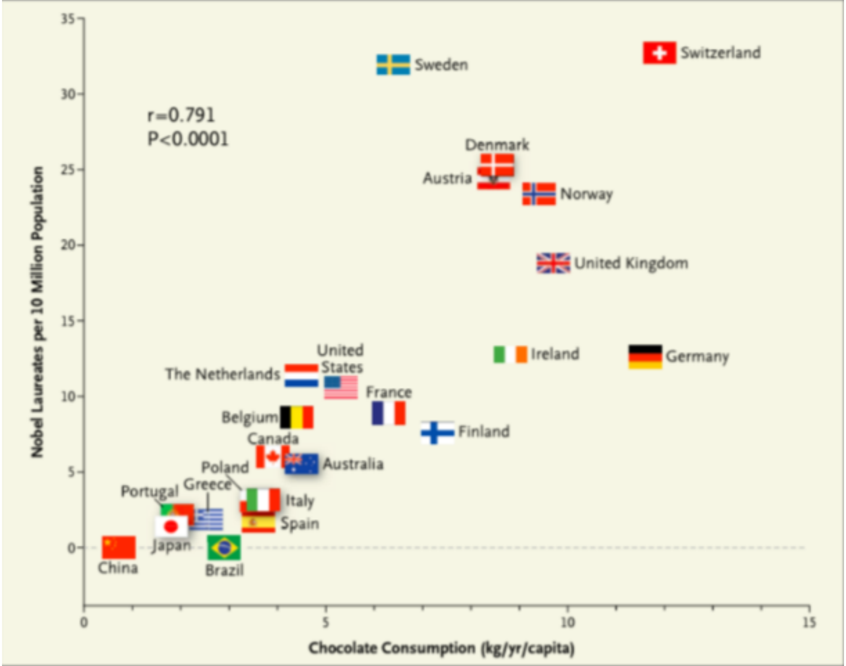


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

Learning from Data

- Why isn't correlation enough?

Learning from Data

- 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

Learning from Data

- 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

Learning from Data

- 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

Section 2

Causal Inference

Causal Inference

- A focus on a single explanatory variable D requires us to clearly define this 'treatment'

Causal Inference

- A focus on a single explanatory variable D requires us to clearly define this 'treatment'
- AND to clearly define a control

Causal Inference

- 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?

Causal Inference

- 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?

Causal Inference

- 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:

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

Causal Inference

- Defining our outcome is also crucial:

Causal Inference

- Defining our outcome is also crucial:
    - Can we measure our outcome of interest?

Causal Inference

- Defining our outcome is also crucial:
  - Can we measure our outcome of interest?
  - Is that outcome the end of the causal chain?

Causal Inference

- Defining our outcome is also crucial:
  - Can we measure our outcome of interest?
  - Is that outcome the end of the causal chain?
  - Tempting to look at many outcomes, but the risk of cherry-picking

Causal Inference

- Defining our outcome is also crucial:
  - Can we measure our outcome of interest?
  - 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

Causal Inference

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

Causal Inference

- 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:

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

Causal Inference

- 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:

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

- Individual Treatment Effect for unit i: $\alpha_i = Y_{1i} - Y_{0i}$

Causal Inference

- 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:

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

- Individual Treatment Effect for unit i: $\alpha_i = Y_{1i} - Y_{0i}$

Causal Inference

- We are relying on **counterfactuals**

Causal Inference

- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?

Causal Inference

- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?
  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?

Causal Inference

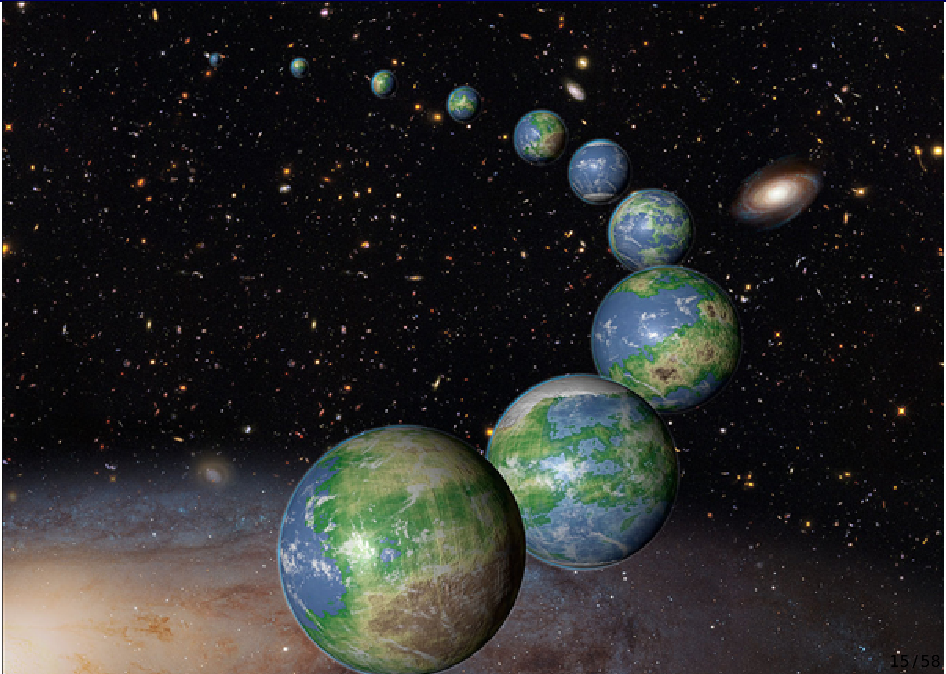
- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?
  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?
  - Would people have voted for Brexit if the campaign had been better regulated?

Causal Inference

- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?
  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?
  - Would people have voted for Brexit if the campaign had been better regulated?
  - Would Brazil have won the 2014 World Cup if Neymar had not been injured?

Causal Inference

- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?
  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?
  - Would people have voted for Brexit if the campaign had been better regulated?
  - Would Brazil have won the 2014 World Cup if Neymar had not been injured?



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	4	1	3
Argentina	7	4	3
Bolivia	2	4	-2
Colombia	7	7	0
Peru	5	4	1

Causal Inference

- Political Science is not about explaining individual events

Causal Inference

- Political Science is not about explaining individual events
- We ideally want general theories that apply to *all our units*

Causal Inference

- Political Science is not about explaining individual events
- We ideally want general theories that apply to *all our units*
- To explain a systematic treatment - not a single event - we need **multiple counterfactual comparisons**

Causal Inference

- Political Science is not about explaining individual events
- We ideally want general theories that apply to *all our units*
- To explain a systematic treatment - not a single event - we need **multiple counterfactual comparisons**
- We know how democracy works in Europe; the question is what will happen if it becomes more common in the whole world?

Causal Inference

- Political Science is not about explaining individual events
- We ideally want general theories that apply to *all our units*
- To explain a systematic treatment - not a single event - we need **multiple counterfactual comparisons**
- We know how democracy works in Europe; the question is what will happen if it becomes more common in the whole world?

Average Treatment Effect

We want to calculate an **Average Treatment Effect**

Causal Inference

- Political Science is not about explaining individual events
- We ideally want general theories that apply to *all our units*
- To explain a systematic treatment - not a single event - we need **multiple counterfactual comparisons**
- We know how democracy works in Europe; the question is what will happen if it becomes more common in the whole world?

Average Treatment Effect

We want to calculate an **Average Treatment Effect**

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

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	4	1	3
Argentina	7	4	3
Bolivia	2	4	-2
Colombia	7	7	0
Peru	5	4	1
Average Treatment Effect	**5**	**4**	**1**

Causal Inference

The Fundamental Problem of Causal Inference

- 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

The Fundamental Problem of Causal Inference

- No units can receive **both** treatment and control
- So we can never observe both Y_1 and Y_0 **for the same unit**
- *Individual* Treatment Effects are **Impossible to Estimate**

Causal Inference

The Fundamental Problem of Causal Inference

- No units can receive **both** treatment and control
- So we can never observe both Y_1 and Y_0 **for the same unit**
- *Individual* Treatment Effects are **Impossible to Estimate**

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

Causal Inference

The Fundamental Problem of Causal Inference

- No units can receive **both** treatment and control
- So we can never observe both Y_1 and Y_0 **for the same unit**
- *Individual* Treatment Effects are **Impossible to Estimate**

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

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

Causal Inference

Potential Outcomes Example

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	4	?	?
Argentina	0	?	4	?
Bolivia	1	2	?	?
Colombia	0	?	7	?
Peru	0	?	4	?

Causal Inference

Potential Outcomes Example

	Democracy?	**Observed** GDP Growth
	D_i	Y^{obs}
Brasil	1	4
Argentina	0	4
Bolivia	1	2
Colombia	0	7
Peru	0	4

Causal Inference

- Actually, nothing stops us calculating the **Average Treatment Effect**

Causal Inference

- Actually, nothing stops us calculating the **Average Treatment Effect**
- The question is, is the ATE accurate?

Causal Inference

- Actually, nothing stops us calculating the **Average Treatment Effect**
- The question is, is the ATE accurate?

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	4	1	3
Argentina	0	7	4	3
Bolivia	1	2	4	-2
Colombia	0	7	7	0
Peru	0	5	4	1
Average Treatment Effect		**5**	**4**	**1**

Causal Inference

- Actually, nothing stops us calculating the **Average Treatment Effect**
- The question is, is the ATE accurate?

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	4	?	?
Argentina	0	?	4	?
Bolivia	1	2	?	?
Colombia	0	?	7	?
Peru	0	?	4	?
Average Treatment Effect		**3**	**5**	**-2**

Causal Inference

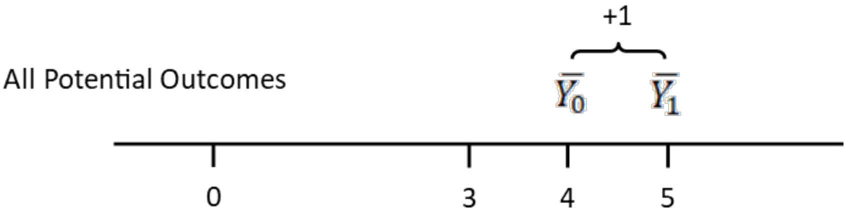
- **So what went wrong?**

Causal Inference

- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units

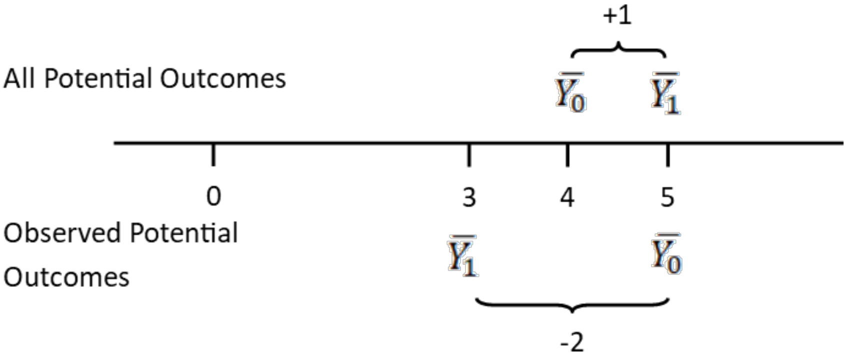
Causal Inference

- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



Causal Inference

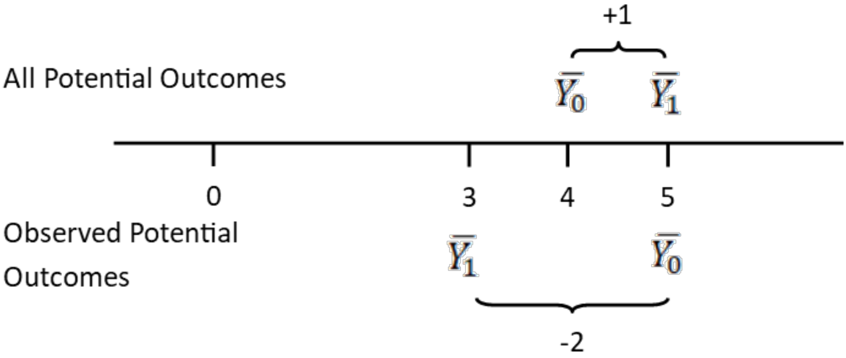
- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



- $E(Y_1)$ values are **biased lower** in the observed data

Causal Inference

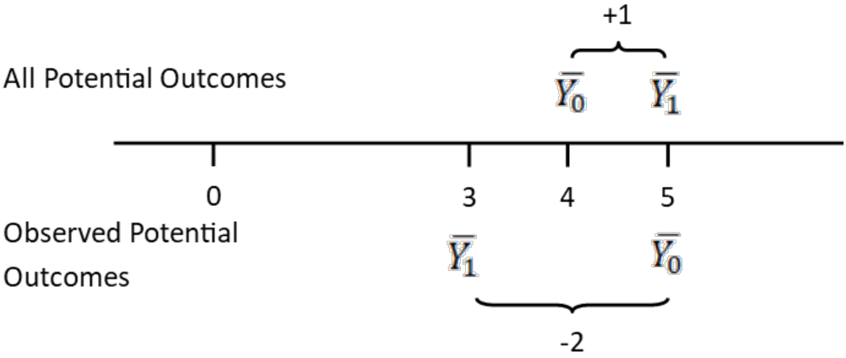
- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



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

Causal Inference

- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



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

Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**

Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- Comparing treated i and control j units

Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- Comparing treated i and control j units
- If potential outcomes are biased in our observed data:

Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- Comparing treated i and control j units
- If potential outcomes are biased in our observed data:
  - Our **counterfactual case** j does not represent what would have happened to i in the absence of treatment

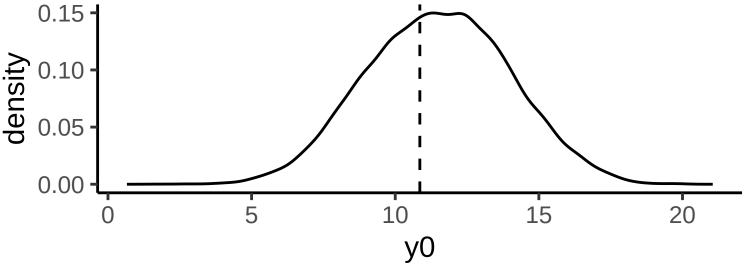
Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- Comparing treated *i* and control *j* units
- If potential outcomes are biased in our observed data:
    - Our **counterfactual case** *j* does not represent what would have happened to *i* in the absence of treatment
    - Counterfactuals are not **plausible**

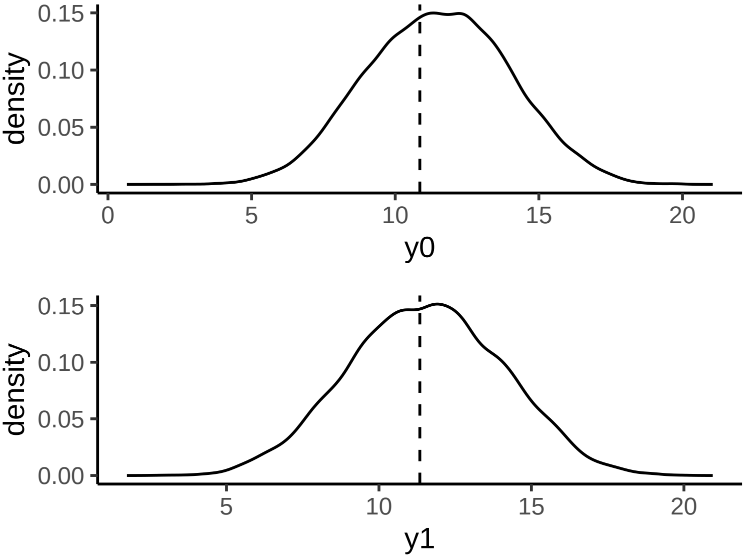
Causal Inference

- The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- Comparing treated i and control j units
- If potential outcomes are biased in our observed data:
  - Our **counterfactual case** j does not represent what would have happened to i in the absence of treatment
  - Counterfactuals are not **plausible**
  - Causal effects are **biased**

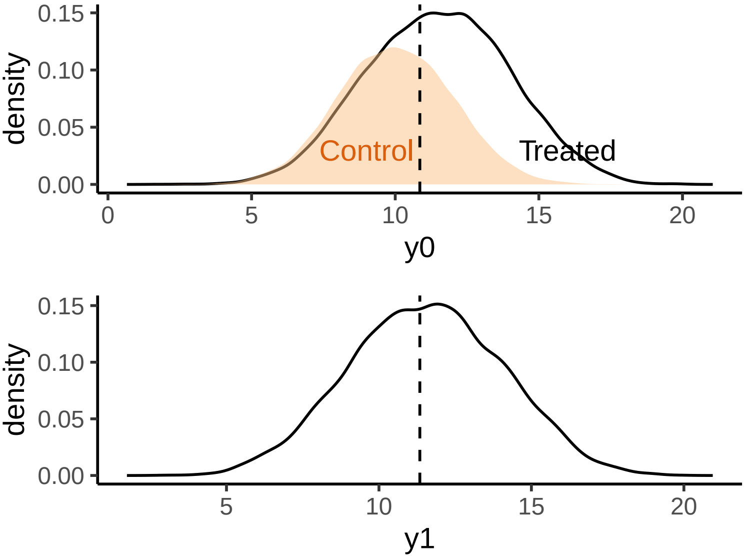
Causal Inference



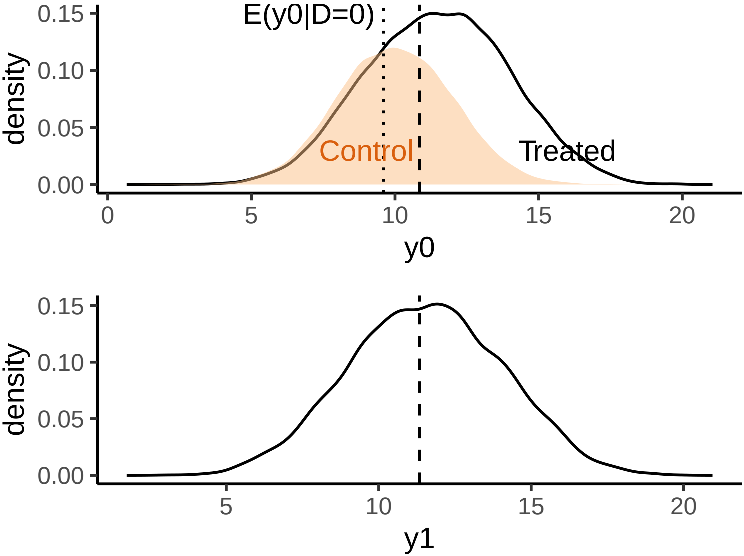
Causal Inference



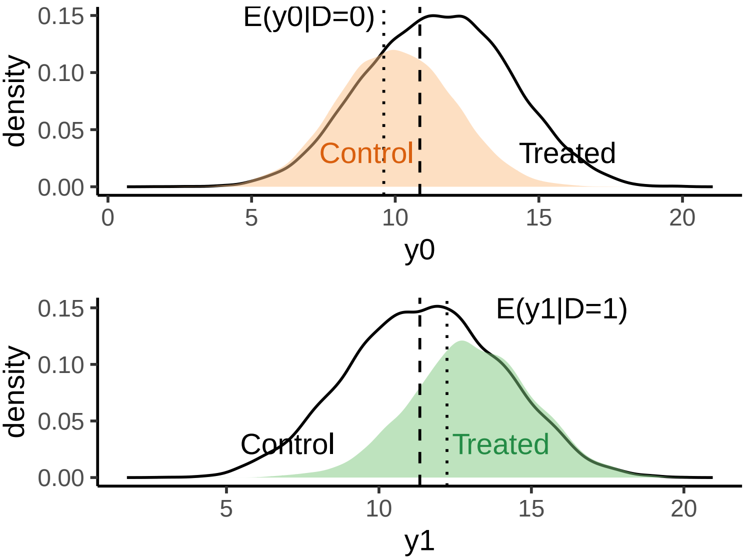
Causal Inference



Causal Inference



Causal Inference



Causal Inference

- Lots of averages:

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

Causal Inference

- Lots of averages:

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

Treatment Assignment Mechanism

- The comparability of treatment and control units depends on *how* they got to be treated

Treatment Assignment Mechanism

- The comparability of treatment and control units depends on *how* they got to be treated
  - On the **Treatment Assignment Mechanism**

Treatment Assignment Mechanism

- The comparability of treatment and control units depends on *how* they got to be treated
  - On the **Treatment Assignment Mechanism**
- If we 'treated' an outlier like the Galapagos Islands, could we find a comparable control unit?

Treatment Assignment Mechanism

- The comparability of treatment and control units depends on *how* they got to be treated
  - 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**

Treatment Assignment Mechanism

- The comparability of treatment and control units depends on *how* they got to be treated
  - 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’

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

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

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

Exercise

- Does fruit make you happier?

Exercise

- Does fruit make you happier?
  - Write down on a piece of paper a number between 0 and 10 representing how happy you would be if I gave you an apple now.

Exercise

- Does fruit make you happier?
  - Write down on a piece of paper a number between 0 and 10 representing how happy you would be if I gave you an apple now.
  - Label this number Y_1.

Exercise

- Does fruit make you happier?
  - Write down on a piece of paper a number between 0 and 10 representing how happy you would be if I gave you an apple now.
  - Label this number Y_1.
  - Then write down a second number between 0 and 10 representing how happy you would be if I did NOT give you an apple now.

Exercise

- Does fruit make you happier?
  - Write down on a piece of paper a number between 0 and 10 representing how happy you would be if I gave you an apple now.
  - Label this number Y_1.
  - Then write down a second number between 0 and 10 representing how happy you would be if I did NOT give you an apple now.
  - Label this number Y_0.

Exercise

- Does fruit make you happier?
  - Write down on a piece of paper a number between 0 and 10 representing how happy you would be if I gave you an apple now.
  - Label this number Y_1.
  - Then write down a second number between 0 and 10 representing how happy you would be if I did NOT give you an apple now.
  - Label this number Y_0.
- These are your **potential outcomes**.

Exercise

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

Exercise

- Now we will consider how estimates of the average effect of fruit on happiness vary depending on how treatment (apples) are assigned.
  1. All the female participants are given an apple.

Exercise

- Now we will consider how estimates of the average effect of fruit on happiness vary depending on how treatment (apples) are assigned.
  1. All the female participants are given an apple.
  2. The tallest half are given an apple.

Exercise

- Now we will consider how estimates of the average effect of fruit on happiness vary depending on how treatment (apples) are assigned.
  1. All the female participants are given an apple.
  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.
    1. All the female participants are given an apple.
    2. The tallest half are given an apple.
    3. You are free to choose yourself to take an apple or not.
    4. Apples are distributed randomly

Section 3

3 Critiques

3 Critiques

- Why are potential outcomes biased in our data?

3 Critiques

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

3 Critiques

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

3 Critiques

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

3 Critiques

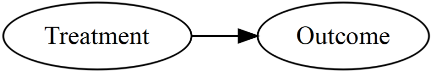
- Why are potential outcomes biased in our data?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- In all of these cases **the potential outcomes are distorted**

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**

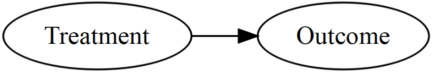
Omitted Variable Bias

A real causal relationship:

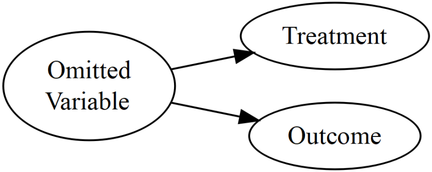


Omitted Variable Bias

A real causal relationship:

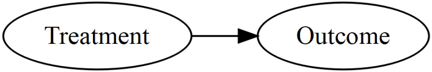


Being misled by omitted variable bias:

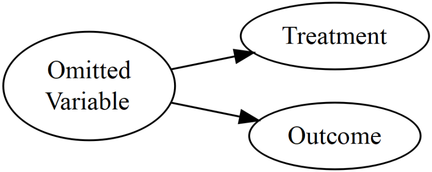


Omitted Variable Bias

A real causal relationship:



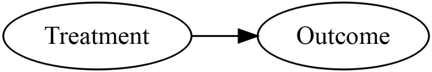
Being misled by omitted variable bias:



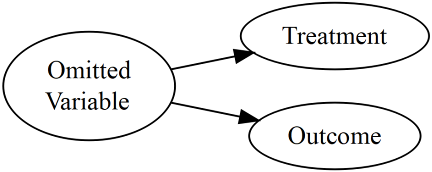
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

Omitted Variable Bias

A real causal relationship:



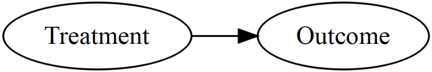
Being misled by omitted variable bias:



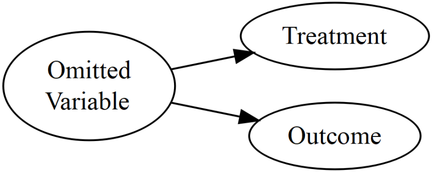
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1

Omitted Variable Bias

A real causal relationship:



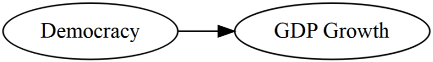
Being misled by omitted variable bias:



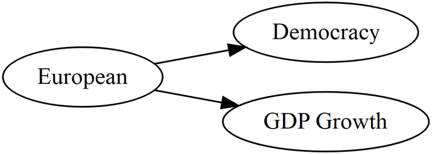
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

Omitted Variable Bias

A real causal relationship:

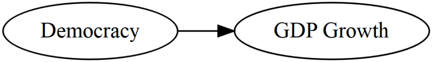


Being misled by omitted variable bias:

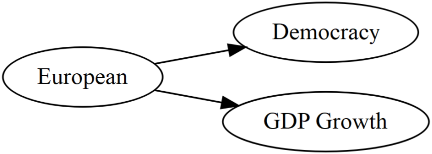


Omitted Variable Bias

A real causal relationship:

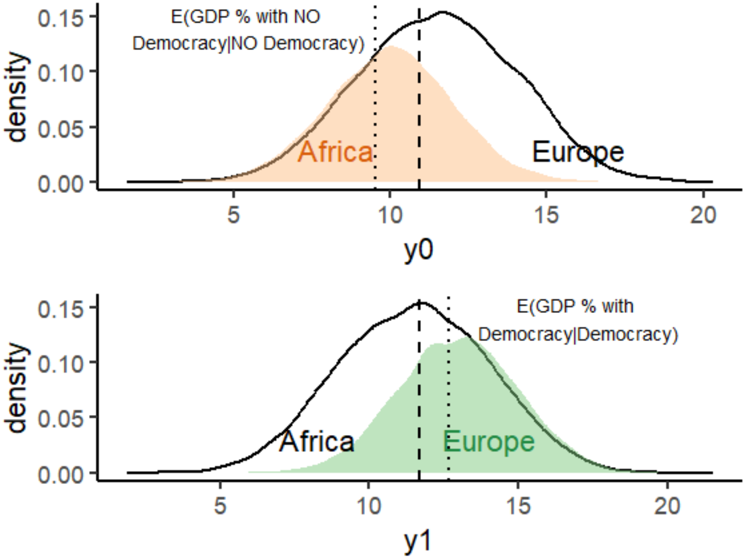


Being misled by omitted variable bias:



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

Omitted Variable Bias



Causal Inference

- Actually, nothing stops us calculating the **Average Treatment Effect**
- The question is, is the ATE accurate?

	Andean?	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Trea Effe**
		D_i	Y_1	Y_0	$Y_1 -$
0	Brasil	0	?	1	?
0	Argentina	0	?	4	?
1	Bolivia	1	2	?	?
1	Colombia	1	7	?	?
1	Peru	1	5	?	?
	Average Treat- ment Effect		**4.7**	**2.5**	**2.2**

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

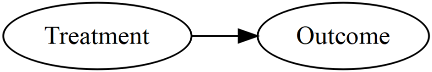
- Let's say that $Y_{1i} = Y_{0i} + \alpha$, where α is the real constant treatment effect

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

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

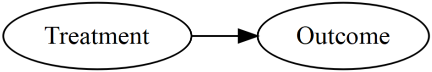
Reverse Causation

A real causal relationship:

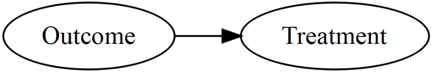


Reverse Causation

A real causal relationship:

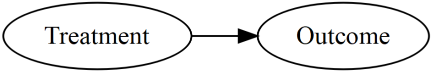


Being misled by reverse causation:

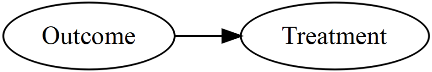


Reverse Causation

A real causal relationship:



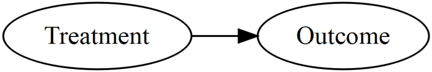
Being misled by reverse causation:



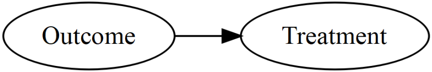
- *D* does not affect *Y*, but higher *Y* makes treatment (*D*) more likely

Reverse Causation

A real causal relationship:



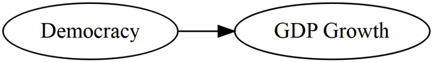
Being misled by reverse causation:



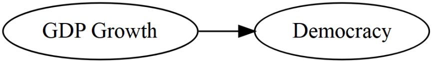
- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are **correlated**

Reverse Causation

A real causal relationship:

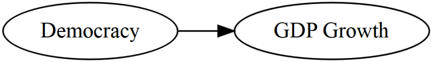


Being misled by reverse causation:

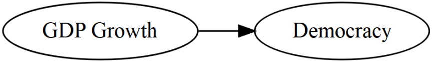


Reverse Causation

A real causal relationship:



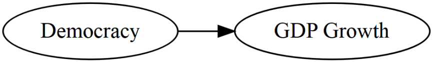
Being misled by reverse causation:



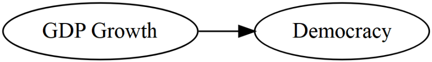
- GDP Growth encourages democratization

Reverse Causation

A real causal relationship:

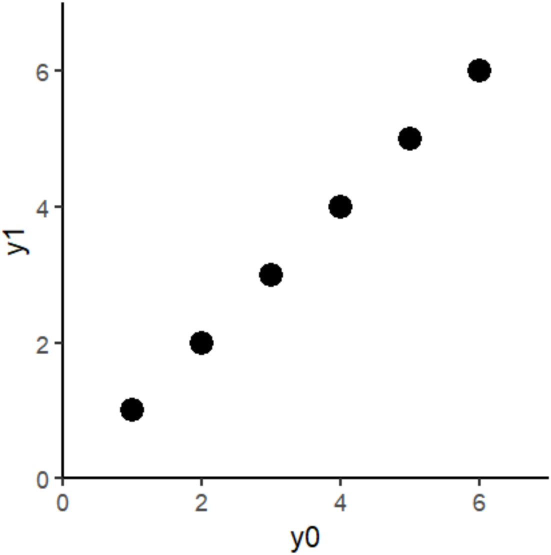


Being misled by reverse causation:



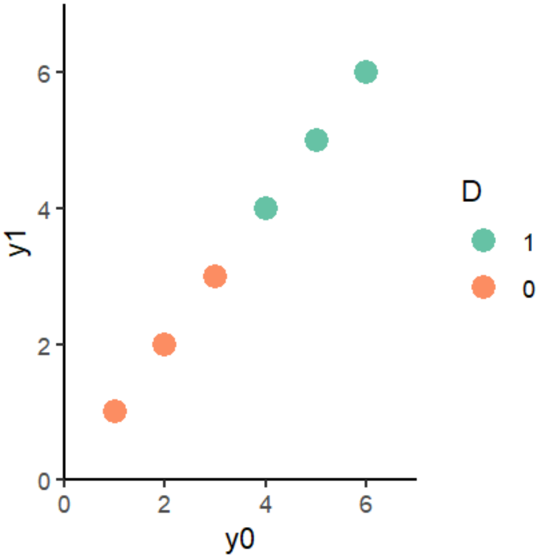
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation

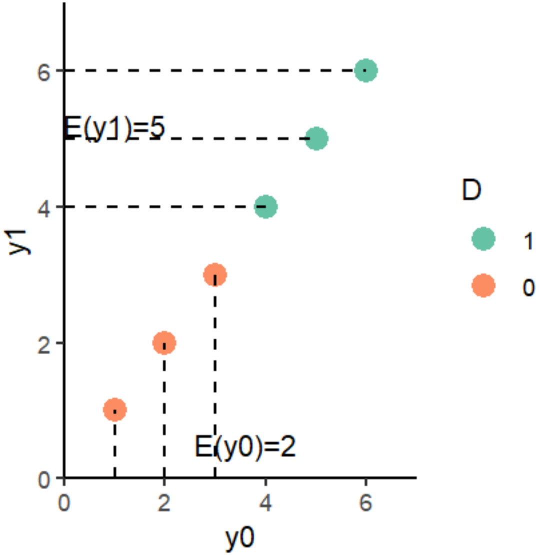


- $E(Y_1 - Y_0) = 0$

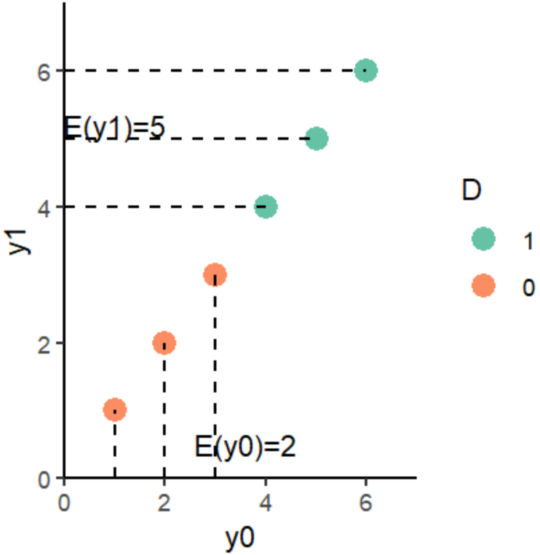
Reverse Causation



Reverse Causation



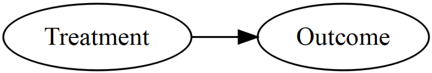
Reverse Causation



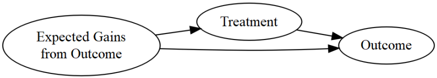
- $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:

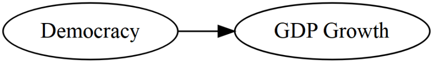


Being misled by Selection Bias:

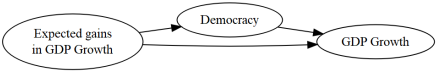


Selection Bias

A real causal relationship:

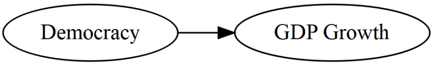


Being misled by Selection Bias:

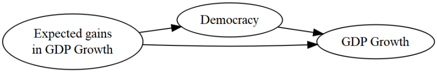


Selection Bias

A real causal relationship:



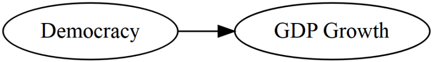
Being misled by Selection Bias:



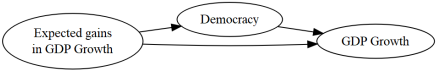
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

A real causal relationship:



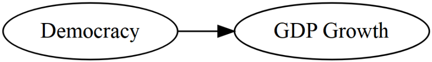
Being misled by Selection Bias:



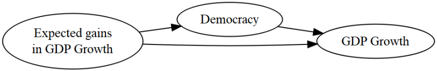
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Selection Bias

A real causal relationship:



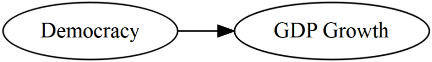
Being misled by Selection Bias:



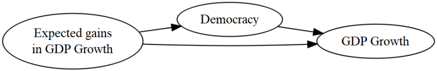
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment
  - Countries which can boost their GDP growth by becoming a democracy choose to democratize

Selection Bias

A real causal relationship:

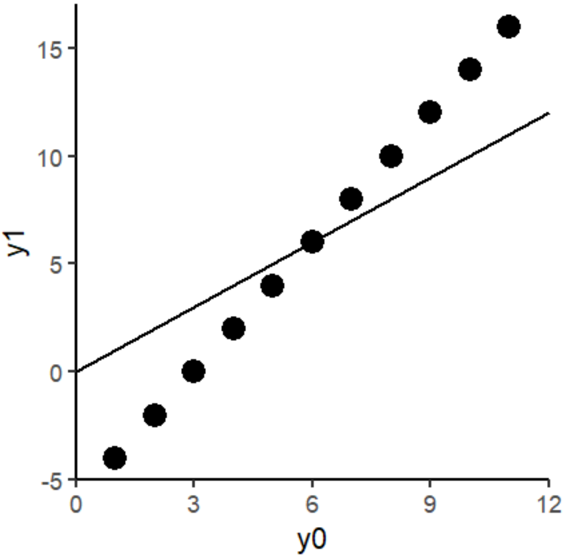


Being misled by Selection Bias:

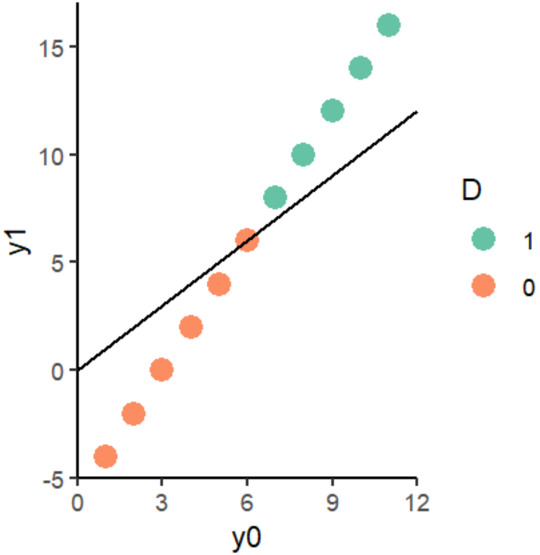


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment
    - Countries which can boost their GDP growth by becoming a democracy choose to democratize
    - Ex. Mexico? Myanmar?

Self-Selection Bias

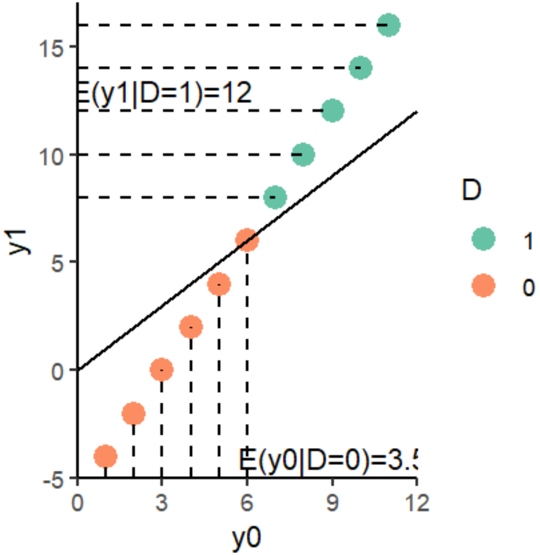


Self-Selection Bias



- $E(y_1) - E(y_0) = 0$

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

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

NB: For equal-sized treatment and control groups

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-Selecion Bias

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

Self-Selecion Bias

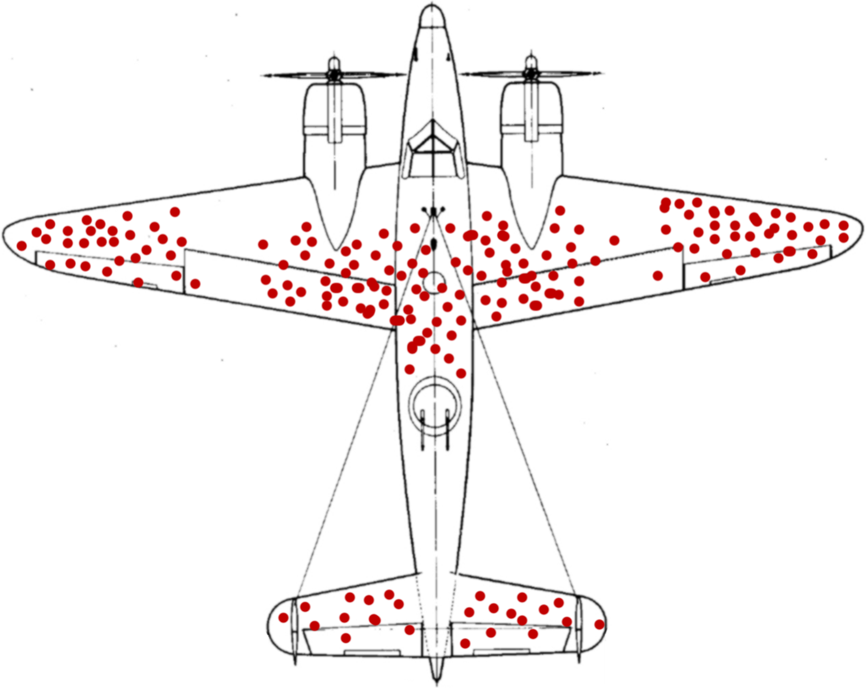
- Selection Bias occurs where our data sample does not tell the complete story:
  1. **Self-selection Bias:** Units that benefit most from treatment choose to receive treatment
     - Those with the biggest difference in potential values, $Y_1 - Y_0$
  2. **Data Availability Bias:** Some types of units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

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*
     - Eg. Wealthy autocracies and poor democracies do not like to report data

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*
     - 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*



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

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
  - This is the **Treatment Assignment Mechanism**

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
  - This is the **Treatment Assignment Mechanism**
- Messy treatment assignment mechanisms are why basic regression is no use for explanation

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
  - This is the **Treatment Assignment Mechanism**
- Messy treatment assignment mechanisms are why basic regression is no use for explanation
  - It means our comparison control cases are really misleading

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
  - This is the **Treatment Assignment Mechanism**
- Messy treatment assignment mechanisms are why basic regression is no use for explanation
  - It means our comparison control cases are really misleading
  - Y_0 for North Korea is not a good guide to the Y_0 for Sweden

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
  - This is the **Treatment Assignment Mechanism**
- Messy treatment assignment mechanisms are why basic regression is no use for explanation
  - It means our comparison control cases are really misleading
  - Y_0 for North Korea is not a good guide to the Y_0 for Sweden
  - What would happen if the control units got treated?

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated
  - Potential outcomes are 'balanced' across control and treatment groups

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated
  - Potential outcomes are 'balanced' across control and treatment groups

Independence of Treatment Assignment

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

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated
  - Potential outcomes are 'balanced' across control and treatment groups

Independence of Treatment Assignment

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

$(Y_1, Y_0) \perp D$

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated
  - Potential outcomes are 'balanced' across control and treatment groups

Independence of Treatment Assignment

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

$(Y_1, Y_0) \perp D$

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

Treatment Assignment Mechanism

- Explanation is more reliable where the **Treatment Assignment Mechanism is Independent of Potential Outcomes**
  - Independent means the values of the potential outcomes give us no information about whether that unit was treated
  - Potential outcomes are 'balanced' across control and treatment groups

Independence of Treatment Assignment

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

$(Y_1, Y_0) \perp D$

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

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

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
Brazil and Bolivia treated	-2
Andean (Omitted Variable Bias)	2.2
Reverse Causation	3
Biggest gains (Self-selection)	8.5

3 Critiques

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

3 Critiques

- *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