Interpreting and Critiquing Causal Evidence

Day 2 - Fundamental Critiques

Jonathan Phillips

January 30, 2024

Section 1

Introduction

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?
- Case studies generally do not

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?
- Case studies generally do not
  - Yes, a case study can confirm that the presence of a treatment coincides with an outcome - it can generate a hypothesis

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?
- Case studies generally do not
  - Yes, a case study can confirm that the presence of a treatment coincides with an outcome - it can generate a hypothesis
  - But the only way to *confirm* a hypothesis is to verify that the pattern repeats, and that the absence of the treatment does not produce the same outcome

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?
- Case studies generally do not
  - Yes, a case study can confirm that the presence of a treatment coincides with an outcome - it can generate a hypothesis
  - But the only way to *confirm* a hypothesis is to verify that the pattern repeats, and that the absence of the treatment does not produce the same outcome
  - For example, a case study of India could conclude large countries produce successful democracies in Asia

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Which methodologies meet these benchmarks?
- Case studies generally do not
  - Yes, a case study can confirm that the presence of a treatment coincides with an outcome - it can generate a hypothesis
  - But the only way to *confirm* a hypothesis is to verify that the pattern repeats, and that the absence of the treatment does not produce the same outcome
  - For example, a case study of India could conclude large countries produce successful democracies in Asia
    - But...China
    - But...South Korea

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Different methodologies have different strengths/roles

Learning from Data

- Now we know the benchmarks for a **convincing explanation** and **strong evidence**
- Different methodologies have different strengths/roles

	Process tracing methodologies	Variation-based methodologies
Type of data	Causal process observations	Dataset observations
Informs us about mechanisms?	Yes	No
Considers the counterfactual?	No	Yes
Ideal type of question:	How?	Does?

Learning from Data

- Variation-based methodologies depend on correlation

Learning from Data

- Variation-based methodologies depend on correlation
- **But correlation is not causation**

Learning from Data

- Variation-based methodologies depend on correlation
- **But correlation is not causation**
  - If we look hard enough we can always find correlations

Learning from Data

- Variation-based methodologies depend on correlation
- **But correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...

Learning from Data

- Variation-based methodologies depend on correlation
- **But correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...

Learning from Data

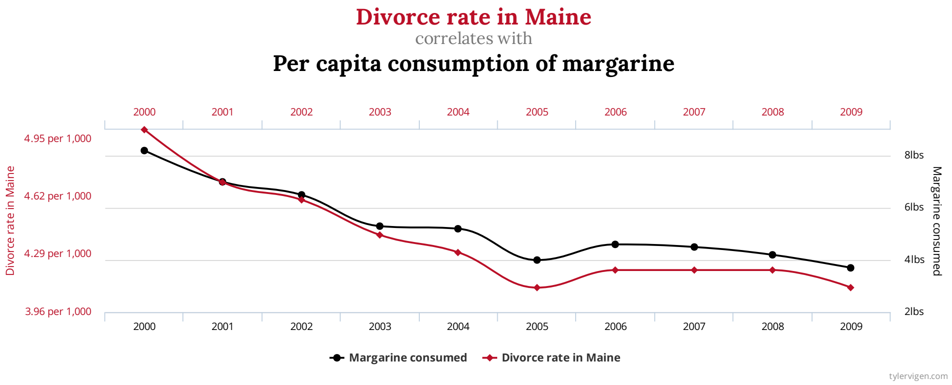
- Variation-based methodologies depend on correlation
- **But correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...
  - But we cannot conclude that there is a causal effect of D on Y

Learning from Data

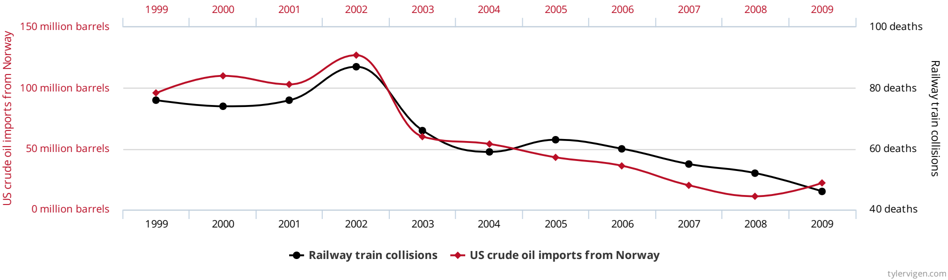
- Variation-based methodologies depend on correlation
- **But correlation is not causation**
  - If we look hard enough we can always find correlations
  - By chance...
  - Due to complex social patterns...
  - But we cannot conclude that there is a causal effect of D on Y
- *More* data will not help

Learning from Data

- Variation-based methodologies depend on correlation
- **But 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

US crude oil imports from Norway
correlates with
Drivers killed in collision with railway train



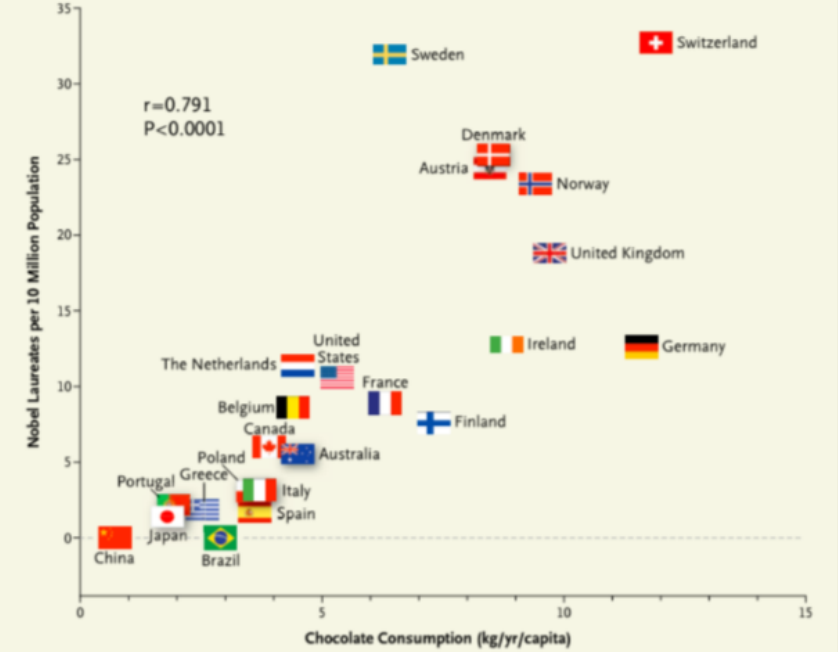


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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?
  - 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?
  - 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

- 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*: $\alpha_i = Y_{1i} - Y_{0i}$
- How much do you like fruit?

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

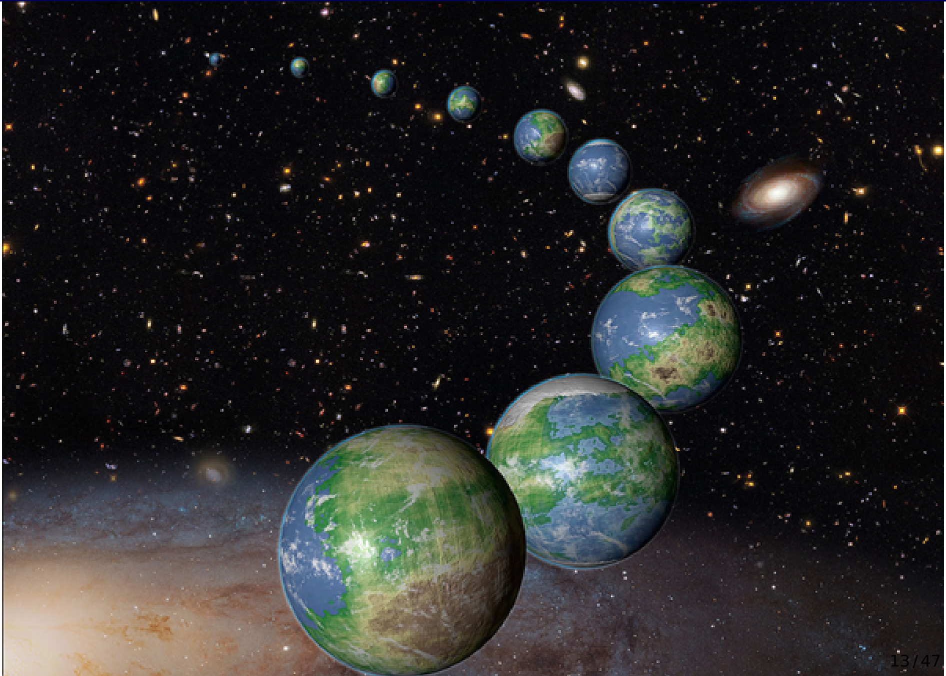
- We are relying on **counterfactuals**
  - What would have happened to the same unit if the treatment had not happened?
  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?
  - Would people have voted for Brexit if the campaign had been better regulated?

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	6	3	3
Argentina	8	5	3
Uruguay	3	3	0
Bolivia	0	2	-2
Colombia	4	4	0
Peru	4	2	2

Causal Inference

- We ideally want general theories that apply to *all our units*

Causal Inference

- 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

- 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**

Average Treatment Effect

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

Causal Inference

- 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**

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	6	3	3
Argentina	8	5	3
Uruguay	3	3	0
Bolivia	0	2	-2
Colombia	4	4	0
Peru	4	2	2
Average Treatment Effect	**4.17**	**3.17**	**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	0	?	3	?
Argentina	0	?	5	?
Uruguay	0	?	3	?
Bolivia	1	0	?	?
Colombia	1	4	?	?
Peru	0	?	2	?

Causal Inference

Potential Outcomes Example

	Democracy?	**Observed** GDP Growth
	D_i	Y^{obs}
Brasil	0	3
Argentina	0	5
Uruguay	0	3
Bolivia	1	0
Colombia	1	4
Peru	0	2

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	0	6	3	3
Argentina	0	8	5	3
Uruguay	0	3	3	0
Bolivia	1	0	2	-2
Colombia	1	4	4	0
Peru	0	4	2	2
Average Treatment Effect		**4.17**	**3.17**	**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	0	?	3	?
Argentina	0	?	5	?
Uruguay	0	?	3	?
Bolivia	1	0	?	?
Colombia	1	4	?	?
Peru	0	?	2	?
Average Treatment Effect		**2**	**3.25**	**-1.25**

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

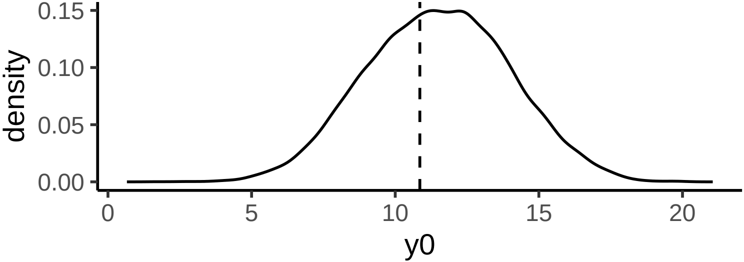
Causal Inference

- **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

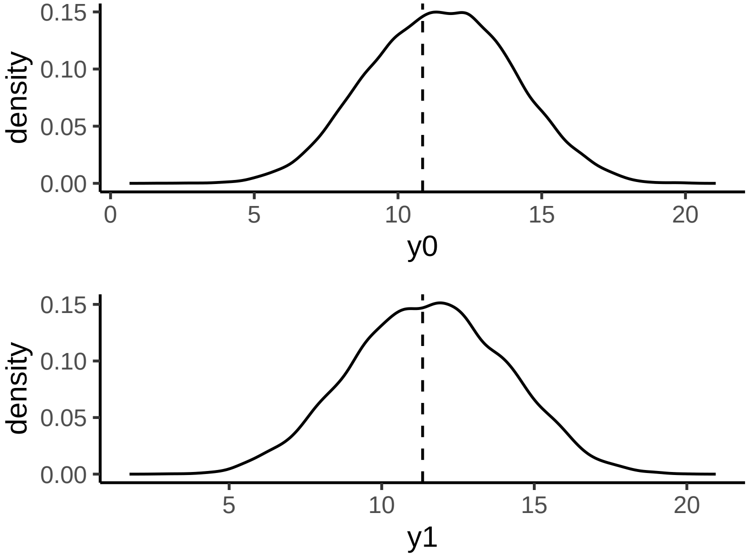
Causal Inference

- **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**

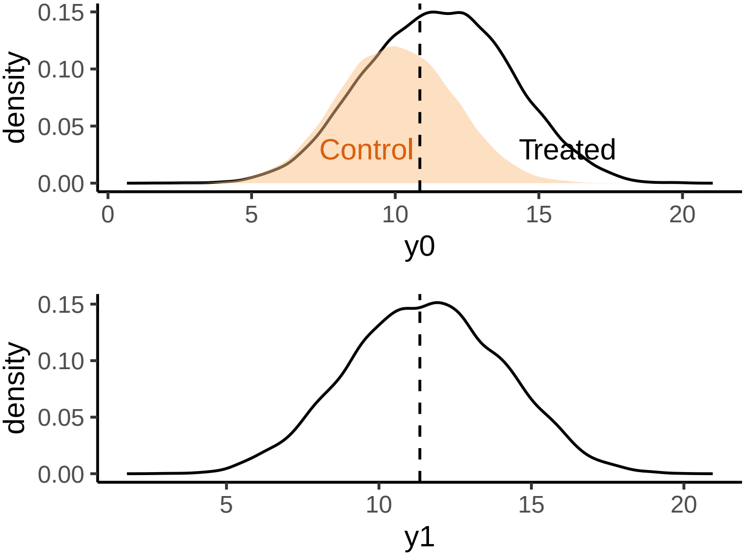
Causal Inference



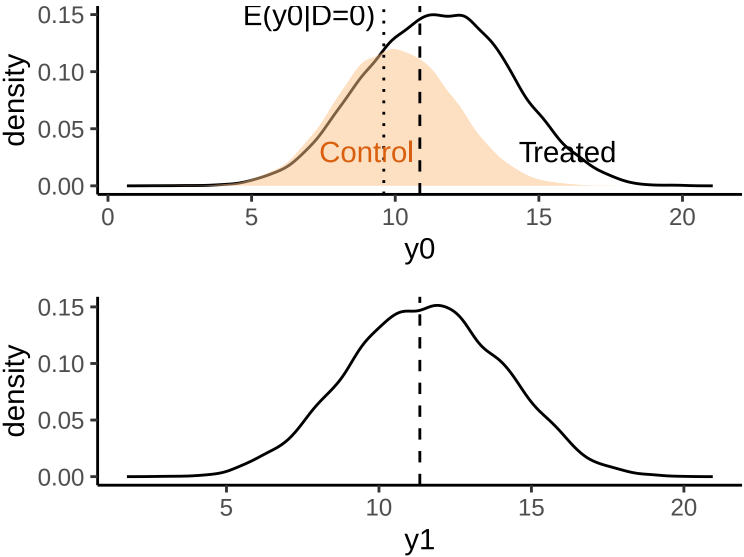
Causal Inference



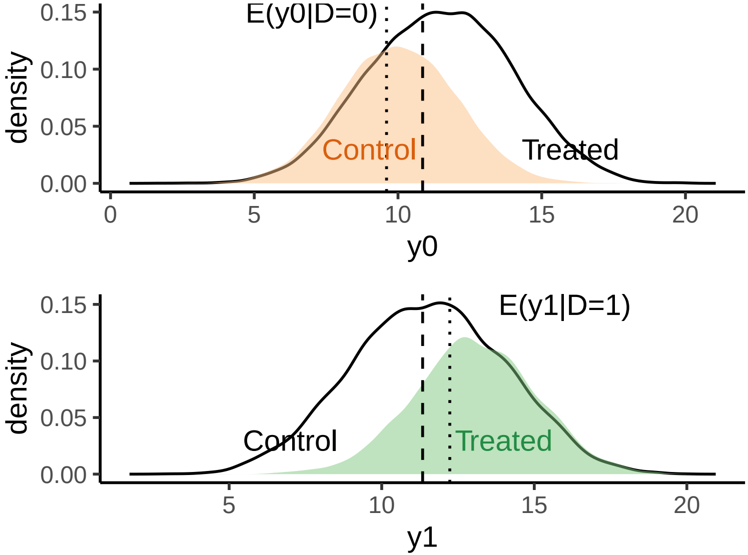
Causal Inference



Causal Inference



Causal Inference



Causal Inference

- If potential outcomes are biased in our observed data:

Causal Inference

- 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

- 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

- 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**

Section 3

Treatment Assignment

Treatment Assignment Mechanism

- When are the treated and control groups likely to be comparable?

Treatment Assignment Mechanism

- When are the treated and control groups likely to be comparable?
  - It depends on *how* they got to be treated

Treatment Assignment Mechanism

- When are the treated and control groups likely to be comparable?
    - It depends on *how* they got to be treated
    - On the **Treatment Assignment Mechanism**

Treatment Assignment Mechanism

- When are the treated and control groups likely to be comparable?
  - It 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

- When are the treated and control groups likely to be comparable?
  - It 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

- When are the treated and control groups likely to be comparable?
  - It 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 the treatment affects you
  - This makes it more likely that potential outcomes are 'balanced'/'representative'

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
  - Except in an experiment

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
  - Except in an experiment

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
  - Except in an experiment
- So we do not know which units might be appropriate counterfactuals

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
- $(Y_1, Y_0) \perp D$
- $Pr(D|(Y_1, Y_0)) = Pr(D)$
- $E(Y|D=1) = E(Y|D=0) = E(Y)$

Section 4

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

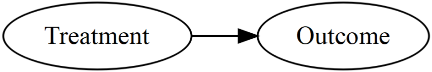
- Why are potential outcomes biased in our data?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- In all of these cases **the potential outcomes are distorted**

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**

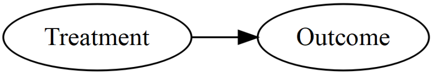
Omitted Variable Bias

A real causal relationship:

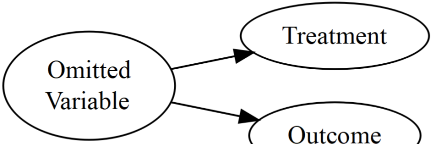


Omitted Variable Bias

A real causal relationship:

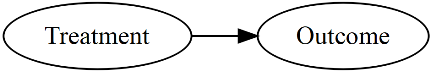


Being misled by omitted variable bias:

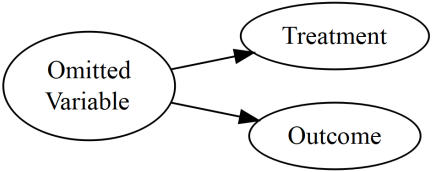


Omitted Variable Bias

A real causal relationship:



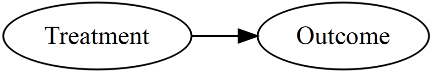
Being misled by omitted variable bias:



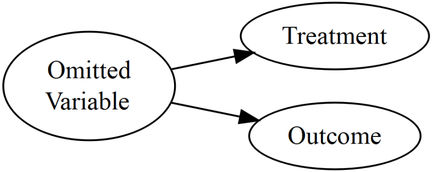
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

Omitted Variable Bias

A real causal relationship:



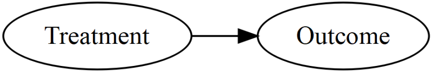
Being misled by omitted variable bias:



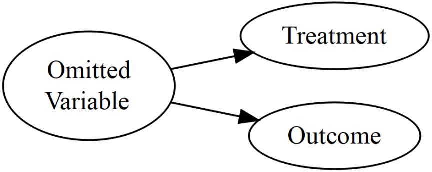
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1

Omitted Variable Bias

A real causal relationship:



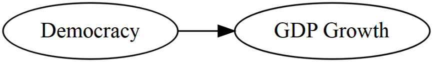
Being misled by omitted variable bias:



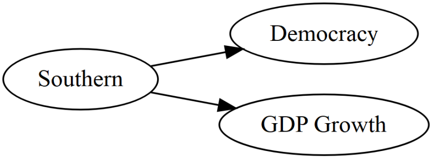
- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

Omitted Variable Bias

A real causal relationship:

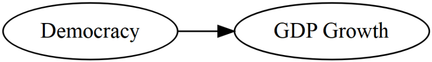


Being misled by omitted variable bias:

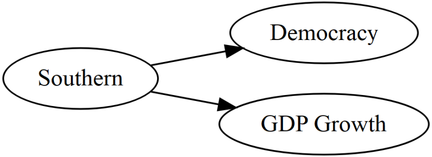


Omitted Variable Bias

A real causal relationship:

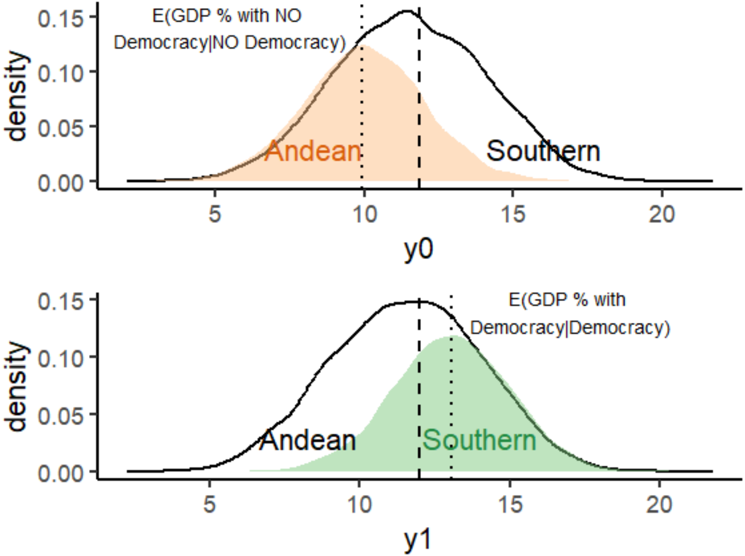


Being misled by omitted variable bias:



- 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

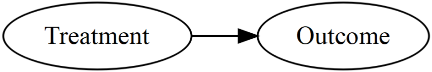
- Let's say that $Y_{1i} = Y_{0i} + \alpha$, where α is the real constant treatment effect

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

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

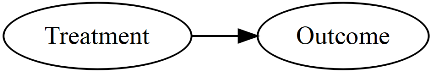
Reverse Causation

A real causal relationship:

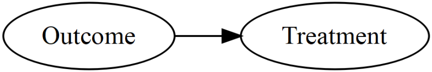


Reverse Causation

A real causal relationship:

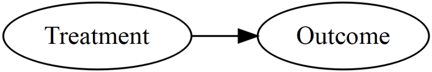


Being misled by reverse causation:

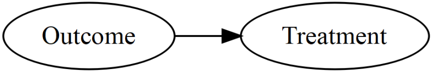


Reverse Causation

A real causal relationship:



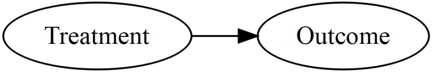
Being misled by reverse causation:



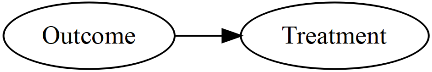
- D does not affect Y, but higher Y makes treatment (D) more likely

Reverse Causation

A real causal relationship:



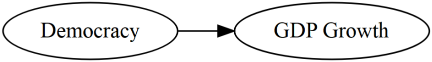
Being misled by reverse causation:



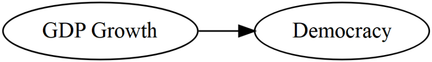
- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are **correlated**

Reverse Causation

A real causal relationship:

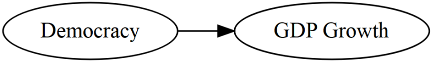


Being misled by reverse causation:

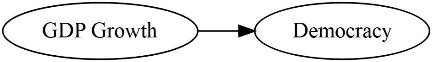


Reverse Causation

A real causal relationship:



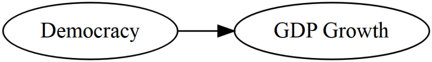
Being misled by reverse causation:



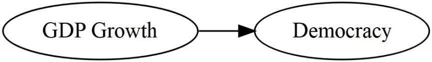
- GDP Growth encourages democratization

Reverse Causation

A real causal relationship:



Being misled by reverse causation:



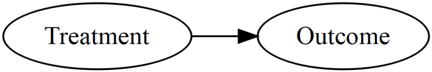
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Causal Inference

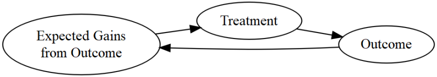
	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	**Treatment Effect**
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	1	4	?	?
Peru	0	?	2	?
Average Treatment Effect		**6**	**2.3**	**3.7**

Selection Bias

A real causal relationship:

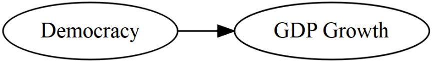


Being misled by Selection Bias:

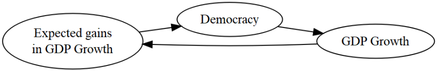


Selection Bias

A real causal relationship:

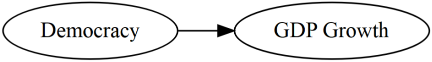


Being misled by Selection Bias:

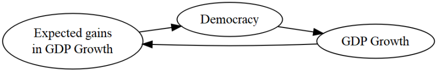


Selection Bias

A real causal relationship:



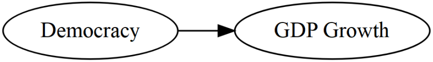
Being misled by Selection Bias:



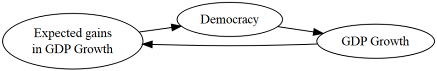
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

A real causal relationship:



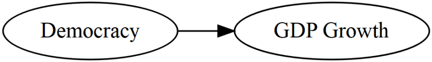
Being misled by Selection Bias:



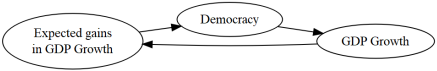
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Selection Bias

A real causal relationship:



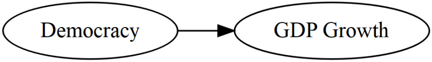
Being misled by Selection Bias:



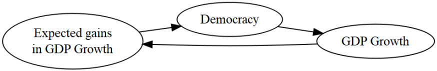
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment
  - Countries which can boost their GDP growth by becoming a democracy choose to democratize

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? 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

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

Self-Selecion Bias

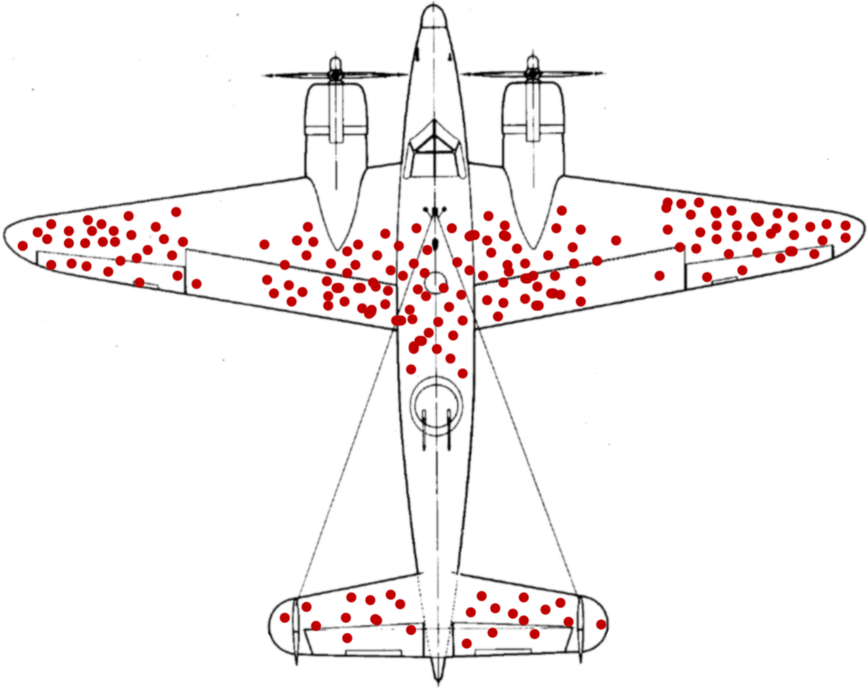
- Selection Bias occurs where our data sample does not tell the complete story:
  1. **Self-selection Bias:** Units that benefit most from treatment choose to receive treatment
     - Those with the biggest difference in potential values, $Y_1 - Y_0$
  2. **Data Availability Bias:** Some types of units 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
     - Only wealthy democracies 'select' into our sample

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*



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:

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
- In all these cases, treatment assignment is not independent of potential outcomes