3.1 — Problem of Causal Inference

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Contents

Two Types of Uses For Regression

$$Y = \beta(X)$$

where Y is numeric:

1. **Causal inference**: estimate $\hat{\beta}$ to determine how changes in X **cause** changes in Y

- Care more about accurately estimating and understanding $\hat{\beta}$
- Remove as much **bias** in $\hat{\beta}$ as possible
- Don't care much about **goodness of fit**! (You'll never get it in the complex real world)

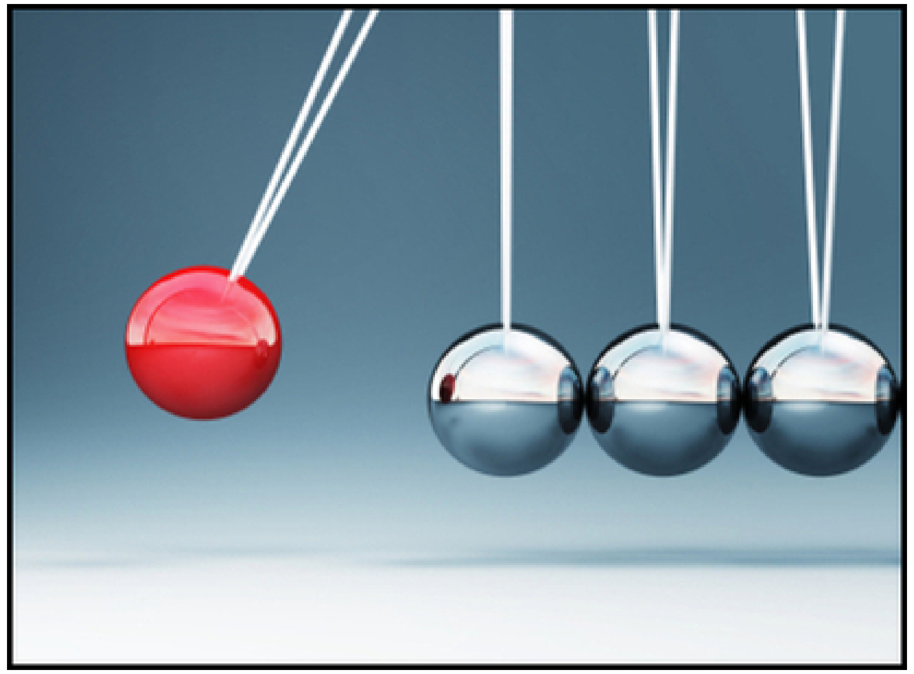
2. **Prediction**: predict $\hat{Y}$ using an estimated $\hat{\beta}$

- Care more about getting $\hat{Y}$ as accurate as possible, $\hat{\beta}$ is an unknown "black-box"
- Tweak models to maximize R^2, minimize $\hat{\sigma}_u$ (at all costs)

Recall: Two Big Problems with Data

- We use econometrics to **identify** causal relationships & make **inferences** about them:

1. Problem for **identification**: **endogeneity**
    - X is **exogenous** if its variation is **unrelated** to other factors (u) that affect Y
    - X is **endogenous** if its variation is **related** to other factors (u) that affect Y
2. Problem for **inference**: **randomness**
    - Data is random due to **natural sampling variation**
    - Taking one sample of a population will yield slightly different information than another sample of the same population



The Two Problems: Identification and Inference

$$\textbf{Sample} \xrightarrow{\text{statistical inference}} \textbf{Population} \xrightarrow{\text{causal indentification}} \textbf{Unobserved Parameters}$$

- We saw how to statistically **infer** values of population parameters using our sample
  - **Purely empirical, math & statistics** 🤓
- We now confront the problem of **identifying** causal relationships within population
  - **Endogeneity problem**
  - Even if we had perfect data on the whole population, **"Does X truly cause Y?"**, and can we measure that effect?
  - **More philosophy & theory than math & statistics!** 🧐
- Truly you should do this first, *before* you get data to make inferences!

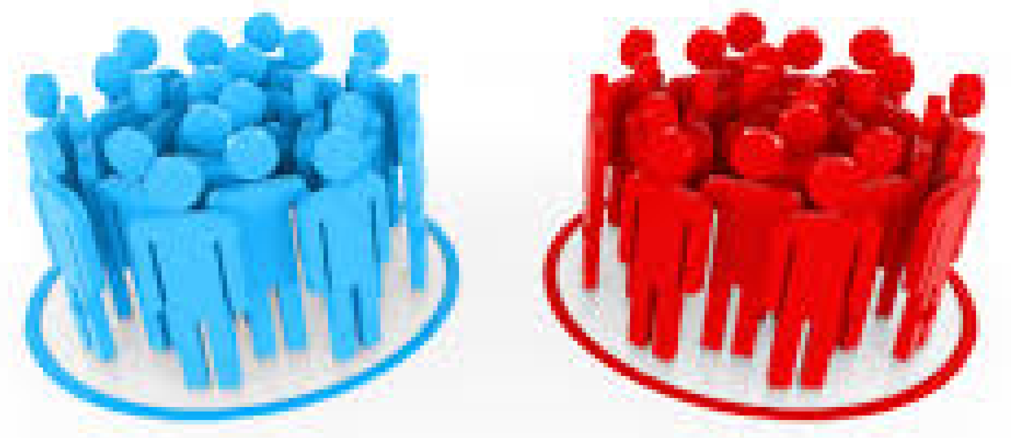
What Does Causation Mean?

- We are going to reflect on one of the biggest problems in **epistemology**, the philosophy of knowledge
- We see that X and Y are **associated** (or quantitatively, **correlated**), but how do we know if **X *causes* Y?**

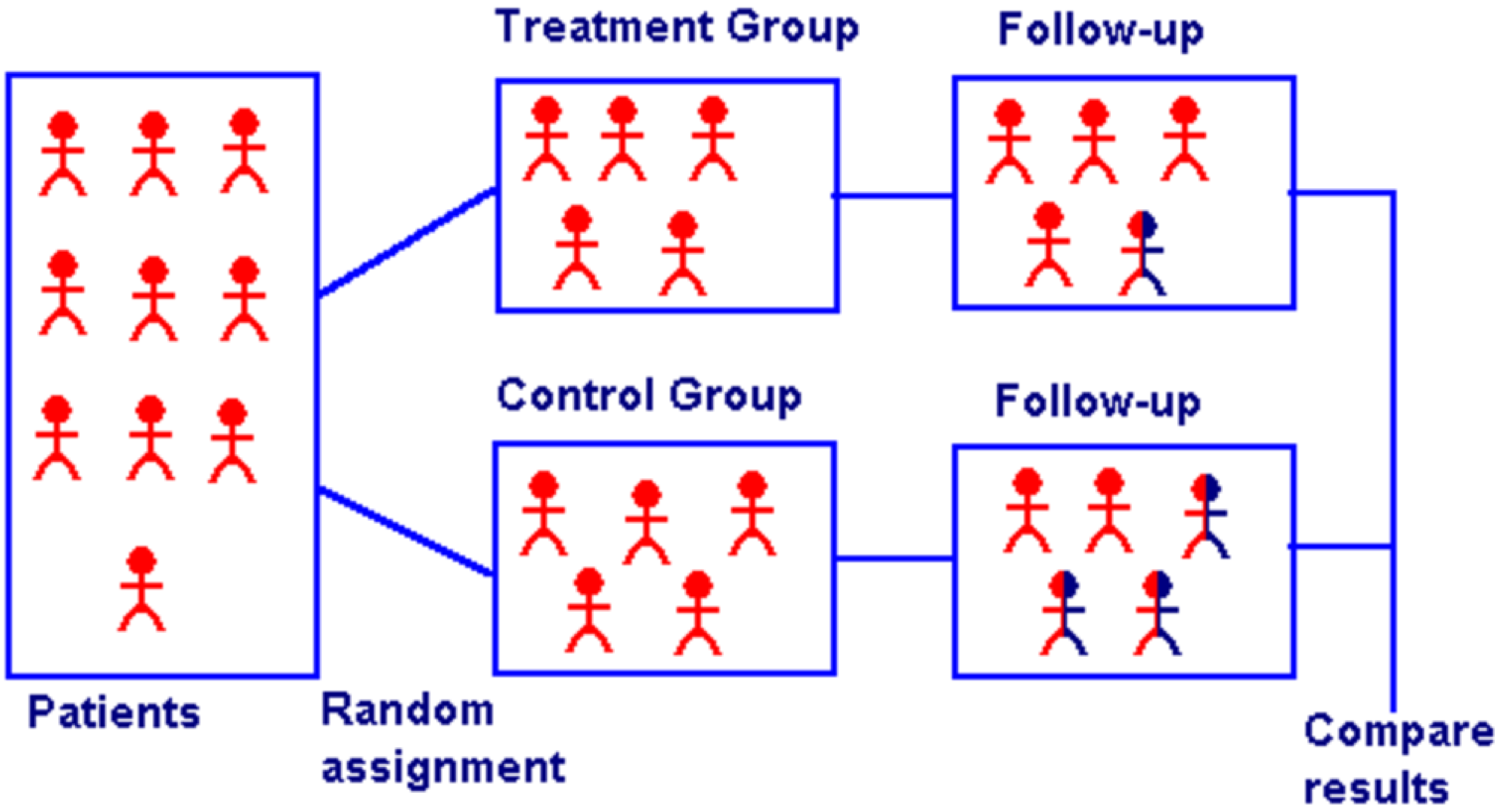
First Pass at Causation: RCTs

Random Control Trials (RCTs) I

- The *ideal* way to demonstrate causation is through a **randomized control trial (RCT)** or **"random experiment"**
  - *Randomly* assign experimental units (e.g. people, firms, etc.) into groups
  - **Treatment group(s)** get a treatment
  - **Control group** gets no treatment
  - Compare average results of treatment vs control groups after treatment o observe the **average treatment effect (ATE)**
- **We will understand "causality" (for now) to mean the ATE from an ideal RCT**



Random Control Trials (RCTs) II



Classic (simplified) procedure of a randomized control trial (RCT) from medicine

Random Control Trials (RCTs) III

Random Control Trials (RCTs) IV

- **Random assignment** to groups ensures that the *only* differences between members of the treatment(s) and control groups is *receiving treatment or not*

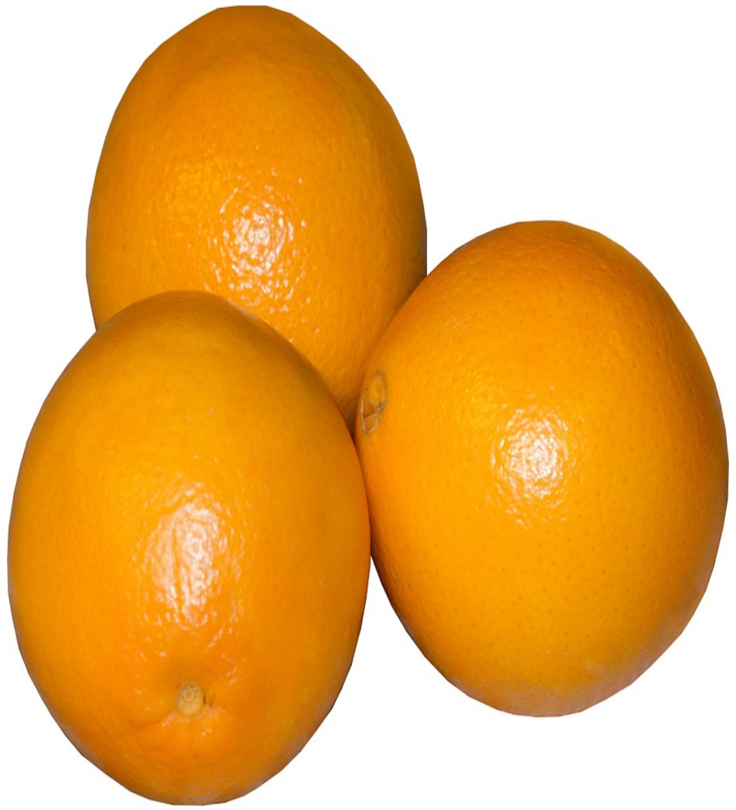
Treatment Group

Control Group

Random Control Trials (RCTs) IV

- **Random assignment** to groups ensures that the *only* differences between members of the treatment(s) and control groups is *receiving treatment or not*
- **Selection bias:** (pre-existing) differences between members of treatment and control groups *other* than treatment, that affect the outcome

Treatment Group



Control Group

The Potential Outcomes Model

The Fundamental Problem of Causal Inference

- Suppose we have some outcome variable Y

- Individuals (i) face a choice between two outcomes (such as being **treated** or **not treated**):
  - Y_i^0: outcome when individual i is **not treated**
  - Y_i^1: outcome when individual i is **treated**

✨ $\delta_i = Y_i^1 - Y_i^0$ ✨

- δ_i is the **causal effect** of treatment on individual i

The Fundamental Problem of Causal Inference

✨ $\delta_i = Y_i^1 - Y_i^0$ ✨

- This is a nice way to think about the ideal proof of causality, but this is impossible to observe!

The Fundamental Problem of Causal Inference

$$\delta_i = ? - Y_i^0$$

- This is a nice way to think about the ideal proof of causality, but this is impossible to observe!
- **Individual counterfactuals do not exist ("the path not taken")**
- You will always only ever get one of these per individual!

The Fundamental Problem of Causal Inference

$$\delta_i = Y_i^1 - ?$$

- This is a nice way to think about the ideal proof of causality, but this is impossible to observe!
- **Individual counterfactuals do not exist ("the path not taken")**
- You will always only ever get one of these per individual!
  - e.g. what would your life have been like if you did not go to Hood College?? 🧐
- So what can we do?

The Fundamental Problem of Causal Inference

$$ATE = \mathbb{E}[Y_i^1] - \mathbb{E}[Y_i^0]$$

- Have large groups, and take *averages* instead!
- **Average Treatment Effect (ATE)**: difference in the average (expected value) of outcome Y between treated individuals and untreated individuals

$$\delta = (\bar{Y}|T = 1) - (\bar{Y}|T = 0)$$

- T_i is a **binary variable**, $= \begin{cases} 0 & \text{if person is not treated} \\ 1 & \text{if person is treated} \end{cases}$

The Fundamental Problem of Causal Inference

$$ATE = \mathbb{E}[Y_i^1] - \mathbb{E}[Y_i^0]$$

Again:

- **Either** we observe individual i in the **treatment group** $(T = 1)$, i.e.

$$\delta_i = Y_i^1 - ?$$

- **Or** we observe individual i in the **control group** $(T = 0)$, i.e.

$$\delta_i = ? - Y_i^0$$

- **Never both** at the same time:

✨ $\delta_i = Y_i^1 - Y_i^0$ ✨

Example: The Effect of Having Health Insurance I

Example

What is the effect of having health insurance on health outcomes?

- National Health Interview Survey (NHIS) asks “Would you say your health in general is excellent, very good, good, fair, or poor?”
- **Outcome variable** (Y): Index of health (1-poor to 5-excellent) in a sample of married NHIS respondents in 2009 who may or may not have health insurance
- **Treatment** (X): Having health insurance (vs. not)

Example: The Effect of Having Health Insurance II

	Husbands			Wives		
	Some HI (1)	No HI (2)	Difference (3)	Some HI (4)	No HI (5)	Difference (6)
			A. Health			
Health index	4.01 [.93]	3.70 [1.01]	.31 (.03)	4.02 [.92]	3.62 [1.01]	.39 (.04)
			B. Characteristics			
Nonwhite	.16	.17	−.01 (.01)	.15	.17	−.02 (.01)
Age	43.98	41.26	2.71 (.29)	42.24	39.62	2.62 (.30)
Education	14.31	11.56	2.74 (.10)	14.44	11.80	2.64 (.11)
Family size	3.50	3.98	−.47 (.05)	3.49	3.93	−.43 (.05)
Employed	.92	.85	.07 (.01)	.77	.56	.21 (.02)
Family income	106,467	45,656	60,810 (1,355)	106,212	46,385	59,828 (1,406)
Sample size	8,114	1,281		8,264	1,131	

Angrist, Joshua & Jorn-Steffen Pischke, 2015, *Mostly Harmless Econometrics*

Example: The Effect of Having Health Insurance III

- Y: outcome variable (health index score, 1-5)
- Y_i: health score of an individual i
- Individual i has a choice, leading to one of two outcomes:
  - Y_i^0: individual i has *not* purchased health insurance **("Control")**
  - Y_i^1: individual i has purchased health insurance **("Treatment")**
- $\delta_i = Y_i^1 - Y_i^0$: causal effect for individual i of purchasing health insurance

Example: A Hypothetical Comparison

John	**Maria**
$Y_J^0 = 3$	$Y_M^0 = 5$
$Y_J^1 = 4$	$Y_M^1 = 5$

- John will choose to buy health insurance
- Maria will choose to not buy health insurance

Example: A Hypothetical Comparison

John	Maria
$Y_J^0 = 3$	$Y_M^0 = 5$
$Y_J^1 = 4$	$Y_M^1 = 5$
✨ $\delta_J = 1$	$\delta_M = 0$ ✨

- John will choose to buy health insurance
- Maria will choose to not buy health insurance
- Health insurance improves John's score by 1, has no effect on Maria's score (individual causal effects δ_i)

Example: A Hypothetical Comparison

John	Maria
$Y_J^0 = 3$	$Y_M^0 = 5$
$Y_J^1 = 4$	$Y_M^1 = 5$
✨ $\delta_J = 1$	$\delta_M = 0$ ✨
$Y_J = (Y_J^1) = 4$	$Y_M = (Y_M^0) = 5$

- John will choose to buy health insurance
- Maria will choose to not buy health insurance
- Health insurance improves John's score by 1, has no effect on Maria's score (individual causal effects δ_i)
- Note, all we can observe in the data are their health outcomes *after* they have chosen (not) to buy health insurance:

$$Y_J = 4$$
$$Y_M = 5$$

Example: A Hypothetical Comparison

John	Maria
$Y_J^0 = 3$	$Y_M^0 = 5$
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- Note, all we can observe in the data are their health outcomes *after* they have chosen (not) to buy health insurance:

$$Y_J = 4$$
$$Y_M = 5$$

- ***Observed* difference** between John and Maria:

$$Y_J - Y_M = -1$$

Counterfactuals

John	Maria
$Y_J = 4$	$Y_M = 5$

This is all the data we *actually* observe

- Observed difference between John and Maria:

$$Y_J - Y_M = \underbrace{Y_J^1 - Y_M^0}_{=-1}$$

- Recall:
  - John has bought health insurance Y_J^1
  - Maria has not bought insurance Y_M^0
- We don't see the **counterfactuals**:
  - John's score *without* insurance
  - Maria score *with* insurance

Counterfactuals

John	Maria
$Y_J = 4$	$Y_M = 5$

This is all the data we *actually* observe

- Observed difference between John and Maria:

$$Y_J - Y_M = \underbrace{Y_J^1 - Y_M^0}_{=-1}$$

- Algebra trick: add and subtract Y_J^0 to equation:

$$Y_J - Y_M = \underbrace{Y_J^1 - Y_J^0}_{=1} + \underbrace{Y_J^0 - Y_M^0}_{=-2}$$

Counterfactuals

John	Maria
$Y_J = 4$	$Y_M = 5$

This is all the data we *actually* observe

$$Y_J - Y_M = \underbrace{Y_J^1 - Y_J^0}_{=1} + \underbrace{Y_J^0 - Y_M^0}_{=-2}$$

- $Y_J^1 - Y_J^0 = 1$: **Causal effect for John**[1] of buying insurance, δ_J
- $Y_J^0 - Y_M^0 = -2$: Difference between John & Maria pre-treatment, **"selection bias"**

1. This is commonly referred to as **TOT: effect of treatment on the *treated* group**

Selection Bias I

$$Y_J^0 - Y_M^0 \neq 0$$

- **Selection bias:** (pre-existing) differences between members of treatment and control groups *other* than treatment, that affect the outcome
  - i.e. John and Maria *start out* with very *different* health scores before either decides to buy insurance or not ("receive treatment" or not)

John (treated)

Maria (control)

Selection Bias II

$$Y_J^0 - Y_M^0 \neq 0$$

- The choice to get treatment is **endogenous**
- A choice made by optimizing agents
- John and Maria have different preferences, endowments, & constraints that cause them to make different decisions

John (treated)

Maria (control)

Example: Our Ideal Data

Ideal (but impossible) Data

Individual	Insured	Not Insured	Diff
John	4.0	3.0	1.0
Maria	5.0	5.0	0.0
Average	4.5	4.0	**0.5**

Example: Our Ideal Data

Ideal (but impossible) Data

Individual	Insured	Not Insured	Diff
John	4.0	3.0	1.0
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Average	4.5	4.0	**0.5**

- **Individual treatment effect** (for individual i):

$$\delta_i = Y_i^1 - Y_i^0$$

Example: Our Ideal Data

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- **Individual treatment effect** (for individual i):

$$\delta_i = Y_i^1 - Y_i^0$$

- ***Average* treatment effect**:

$$ATE = \frac{1}{n}\sum_{i=1}^{n}(Y_i^1 - Y_i^0)$$

Example: Our Ideal Data

Ideal (but impossible) Data			
Individual	**Insured**	**Not Insured**	**Diff**
John	4.0	3.0	1.0
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Average	4.5	4.0	**0.5**

Actual (observed) Data			
Individual	**Insured**	**Not Insured**	**Diff**
John	4.0	?	?
Maria	?	5.0	?
Average	?	?	?

- **Individual treatment effect** (for individual i):

$$\delta_i = Y_i^1 - Y_i^0$$

- ***Average* treatment effect**:

$$ATE = \frac{1}{n}\sum_{i=1}^{n}(Y_i^1 - Y_i^0)$$

- We never get to see each person's **counterfactual** state to compare and calculate ITEs or ATE
  - Maria with insurance Y_M^1
  - John without insurance Y_J^0

Can't We Just Take the Difference of Group Means?

- Can't we just take the difference in group means?

$$diff. = Avg(Y_i^1|T=1) - Avg(Y_i^0|T=0)$$

Actual (observed) Data

Individual	Insured	Not Insured	Diff
John	4.0	?	?
Maria	?	5.0	?
Average	?	?	?

- We never get to see each person's **counterfactual** state to compare and calculate ITEs or ATE
  - Maria with insurance Y_M^1
  - John without insurance Y_J^0

Can't We Just Take the Difference of Group Means?

- Can't we just take the difference in group means?

$$diff. = Avg(Y_i^1|T=1) - Avg(Y_i^0|T=0)$$

- Suppose a uniform treatment effect, δ_i

$$\begin{aligned}
&= Avg(Y_i^1|T=1) - Avg(Y_i^0|T=0) \\
&= Avg(\delta_i + Y_i^0|T=1) - Avg(Y_i^0|T=0) \\
&= \delta_i + \underbrace{Avg(Y_i^0|T=1) - Avg(Y_i^0|T=0)}_{\text{selection bias}} \\
&= ATE + \text{selection bias}
\end{aligned}$$

Actual (observed) Data

Individual	Insured	Not Insured	Diff
John	4.0	?	?
Maria	?	5.0	?
Average	?	?	?

- We never get to see each person's **counterfactual** state to compare and calculate ITEs or ATE
  - Maria with insurance Y_M^1
  - John without insurance Y_J^0

Example: Thinking About the Data

Understanding Selection Bias

- **Treatment group** and **control group** differ on average, for reasons *other* than getting treatment or not!
- **Control group** is not a good counterfactual for **treatment group** without treatment
  - Average *untreated* outcome for the treatment group differs from average untreated outcome for *untreated* group

$$Avg(Y_i^0|T=1) - Avg(Y_i^0|T=0)$$

- Recall we cannot observe $Avg(Y_i^0|T=1)$!

John (treated)

Maria (control)

Understanding Selection Bias: Regression

- Consider the problem in regression form:

$$Y = \beta_0 + \beta_1 T_i + u_i$$

- Where

$$T_i = \begin{cases} 0 & \text{if person is not treated} \\ 1 & \text{if person is treated} \end{cases}$$

- The problem is $cor(T, u) \neq 0$!
  - T_i (Treatment) is endogenous!
  - *Getting* treatment is correlated with other factors that determine health!

John (treated)

Maria (control)

Random Assignment: The Silver Bullet

- If treatment is **randomly assigned** for a large sample, it eliminates selection bias!
- Treatment and control groups differ **on average** by nothing *except* treatment status
- Creates **ceterus paribus** conditions in economics: groups are identical **on average** (holding constant age, sex, height, etc.)

Treatment Group

Control Group

Random Assignment: Regression

- Consider the problem in regression form:

$$Y = \beta_0 + \beta_1 T_i + u_i$$

- If treatment T_i is administered *randomly*, it breaks the correlation with u_i!
  - Treatment becomes **exogenous**!
  - $cor(T, u) = 0$

Treatment Group

Control Group

Natural Experiments

The Quest for Causal Effects I

- RCTs are considered the "gold standard" for causal claims
- But society is not our laboratory (probably a good thing!)
- We can rarely conduct experiments to get data

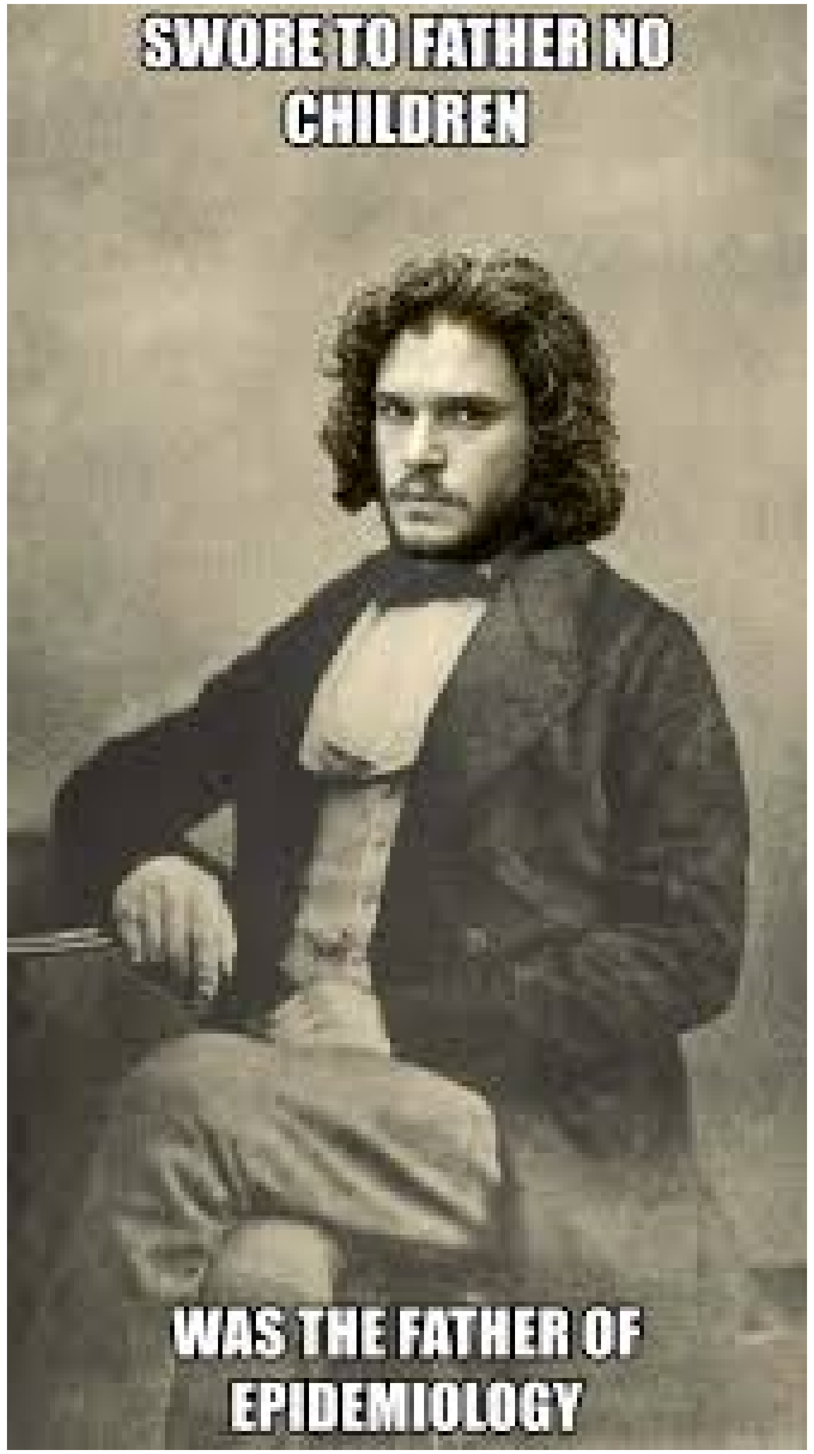
The Quest for Causal Effects II

- Instead, we often rely on **observational data**
- This data is *not random*!
- Must take extra care in forming an **identification strategy**
- To make good claims about causation in society, we must get clever!

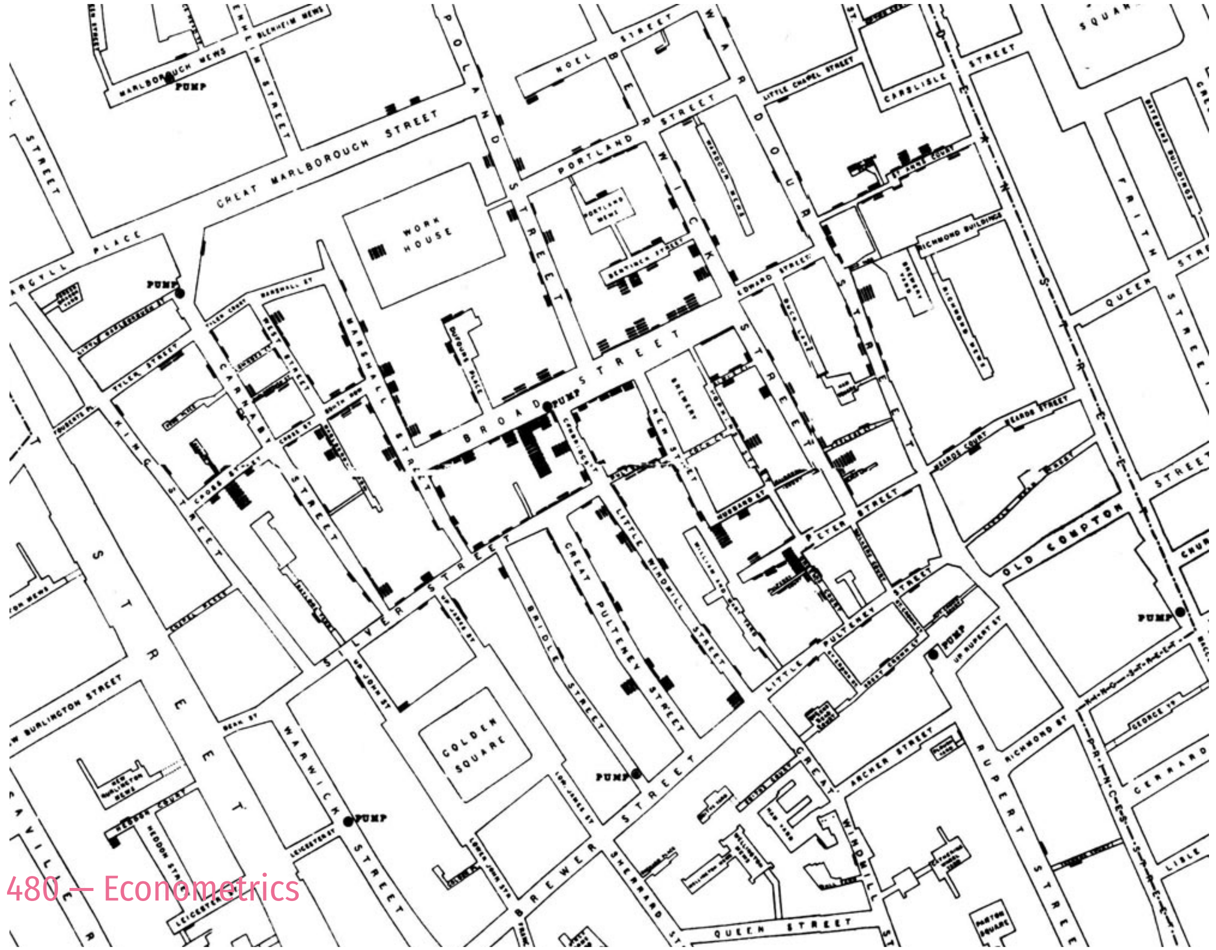
Natural Experiments

- Economists often resort to searching for **natural experiments**
- "Natural" events beyond our control occur that separate *otherwise similar* entities into a "treatment" group and a "control" group that we can compare
- e.g. natural disasters, U.S. State laws, military draft

The First Natural Experiment



- John Snow utilized the first famous natural experiment to establish the foundations of epidemiology and the germ theory of disease
- Water pumps with sources *downstream* of a sewage dump in the Thames river spread cholera while water pumps with sources *upstream* did not



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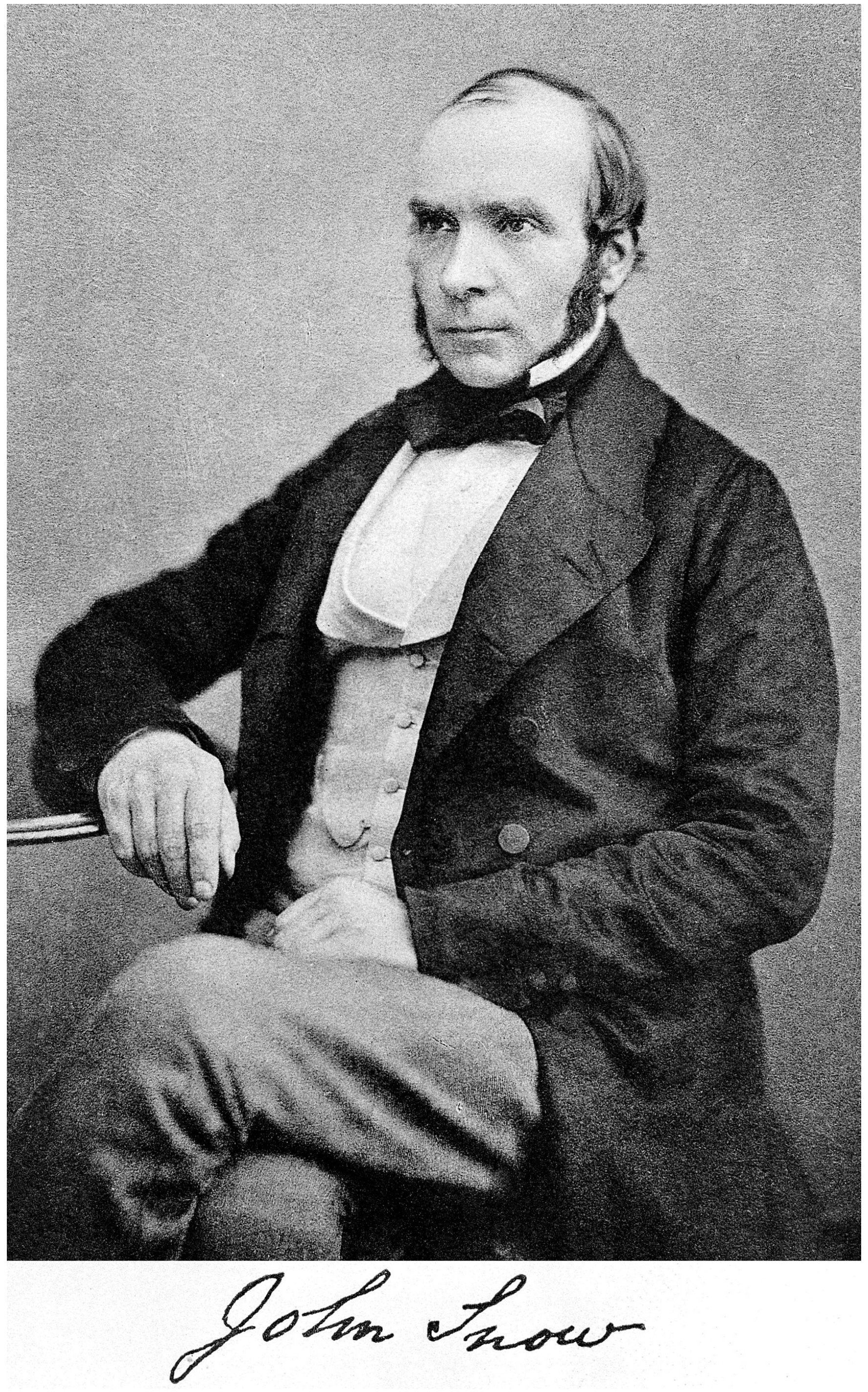

1813-1858

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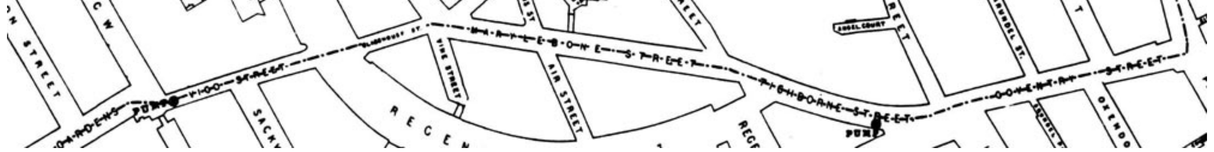

Famous Natural Experiments in Empirical Economics

- **Oregon Health Insurance Experiment**: Oregon used lottery to grant Medicare access to 10,000 people, showing access to Medicaid increased use of health services, lowered debt, etc. relative to those not on Medicaid
- **Angrist (1990)** finds that lifetime earnings of (random) drafted Vietnam veterans is 15% lower than non-veterans
- **Card & Kreuger (1994)** find that minimum wage hike in fast-food restaurants on NJ side of border had no disemployment effects relative to restaurants on PA side of border during the same period
- **Acemoglu, Johnson, and Robinson (2001)** find that inclusive institutions lead to higher economic development than extractive institutions, determined by a colony's disease environment in 1500
- We will look at some of these in greater detail throughout the course
- A great list, with explanations is here

Attack of/on the Randomistas

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rct "gold standard"

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BJOG. Author manuscript; available in PMC 2018 Dec 1.
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Author Manuscript

Randomised controlled trials—the gold standard for effectiveness research

Eduardo Hariton, MD, MBA[1] and Joseph J. Locascio, PhD[2]

Randomized Assignment of Treatment

When a program is assigned at random—that is, using a lottery—over a large eligible population, we can generate a robust estimate of the counterfactual. *Randomized assignment* of treatment is considered the gold standard of impact evaluation. It uses a random process, or chance, to decide who is granted access to the program and who is not.[1] Under randomized assignment, every eligible unit (for example, an individual, household, business,

RCTs are All the Rage

Massachusetts Institute of Technology (MIT)
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Professors Esther Duflo and Abhijit Banerjee, co-directors of MIT's @JPAL, receive congratulations on the big news this morning. They share in the #NobelPrize in economic sciences "for their experimental approach to alleviating global poverty."

Photo: Bryce Vickmark

vox.com

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Empiricism and development economics

The transformation of development economics into an intensely empirical field that leans heavily on randomized controlled trials hasn't been uncontroversial, and many of **the responses** to the Nobel Prize announcement acknowledge that controversy.

Critics have **complained that** randomization feels much more scientific than other approaches but doesn't necessarily answer our questions any more definitively. **Others worry** that the focus on small-scale questions — Do wristbands increase vaccination rates? Do textbooks improve school performance? — might distract us from addressing larger, structural contributors to poverty.

But while new innovations and new methods will doubtless be needed to continue progress against poverty, the practical impact of Kremer, Duflo, and Banerjee's work has already been enormous. As the committee wrote, "The Laureates' research findings — and those of the researchers following in their footsteps — have dramatically improved our ability to fight poverty in practice. As a direct result of one of their studies, more than five million Indian children have benefitted from effective programmes of remedial tutoring in schools."

The three will share a prize worth 9 million Swedish crowns, or $915,300.

The Nobel in economics — technically called the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel — was not established by Alfred Nobel in his will in 1895 but was established in 1968 by a donation from Sweden's central bank and is administered and awarded with the other Nobel Prizes.

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Vox (Oct 14, 2019)

But Not Everyone Agrees I

Angus Deaton

Economics Nobel 2015

> "The RCT is a useful tool, but I think that is a mistake to put method ahead of substance. I have written papers using RCTs... [but] no RCT can ever legitimately claim to have established causality. My theme is that RCTs have no special status, they have no exemption from the problems of inference that econometricians have always wrestled with, and there is nothing that they, and only they, can accomplish."

Deaton, Angus, 2019, "Randomization in the Tropics Revisited: A Theme and Eleven Variations", Working Paper

But Not Everyone Agrees II

Lant Pritchett

> "People keep saying that the recent Nobelists 'studied global poverty.' This is exactly wrong. They made a commitment to a method, not a subject, and their commitment to method prevented them from studying global poverty."

> "At a conference at Brookings in 2008 Paul Romer [2018 Nobelist] said:"You guys are like going to a doctor who says you have an allergy and you have cancer. With the skin rash we can divide you skin into areas and test variety of substances and identify with precision and some certainty the cause. Cancer we have some ideas how to treat it but there are a variety of approaches and since we cannot be sure and precise about which is best for you, we will ignore the cancer and not treat it."

Source

But Not Everyone Agrees III

Angus Deaton

Economics Nobel 2015

> “Lant Pritchett is so fun to listen to, sometimes you could forget that he is completely full of shit.”

[Source](https://medium.com/@ismailalimanik/lant-pritchett-the-debate-about-rcts-in-development-is-over-ec7a28a82c17

RCTs and "Evidence-Based Policy"

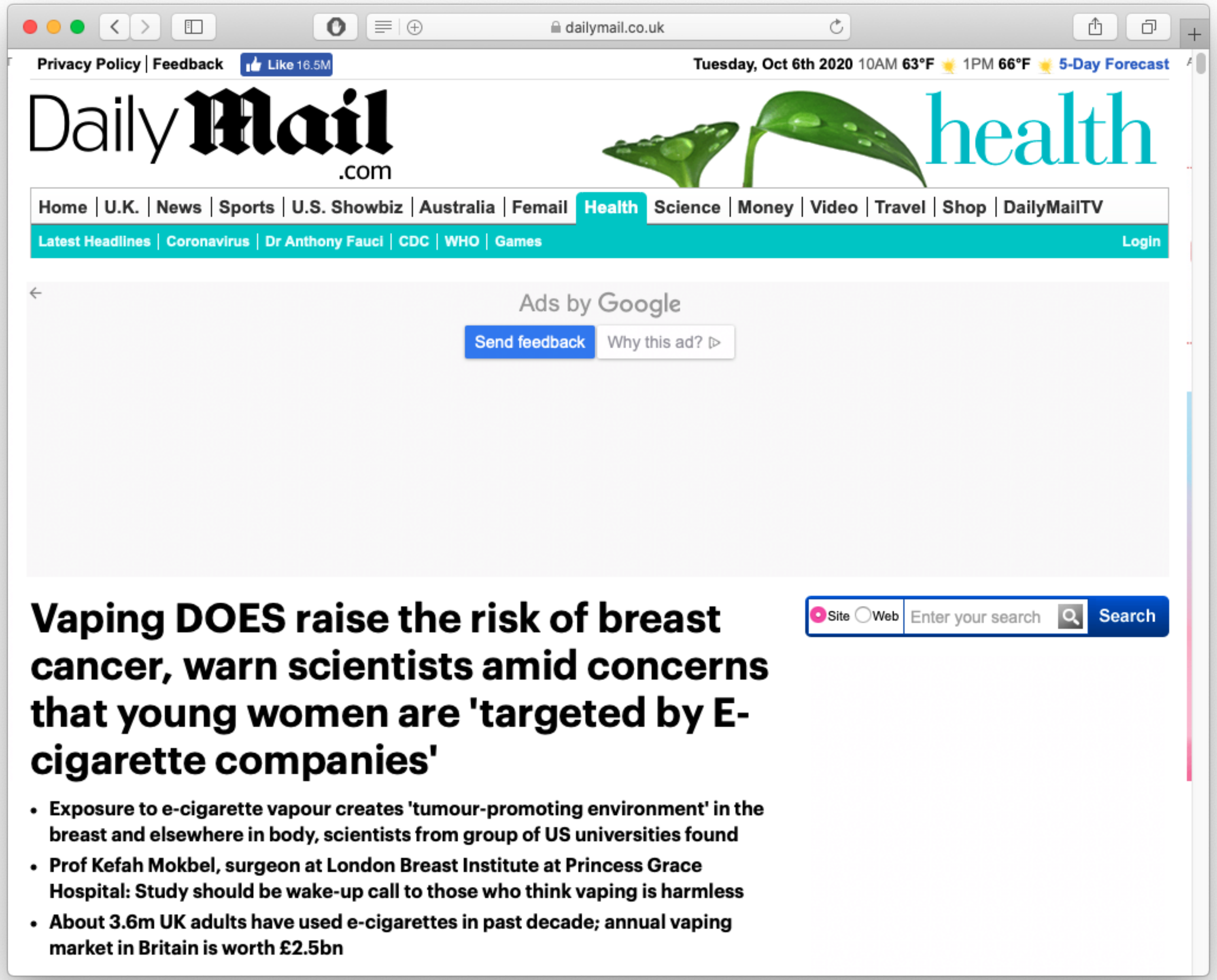
- Programs *randomly* assign treatment to different individuals and measure causal effect of treatment
- **RAND Health Insurance Study**: randomly give people health insurance
- **Oregon Medicaid Expansion**: randomly give people Medicaid
- **HUD's Moving to Opportunity**: randomly give people moving vouchers
- **Tennessee STAR**: randomly assign students to large vs. small classes

RCTs and External Validity I

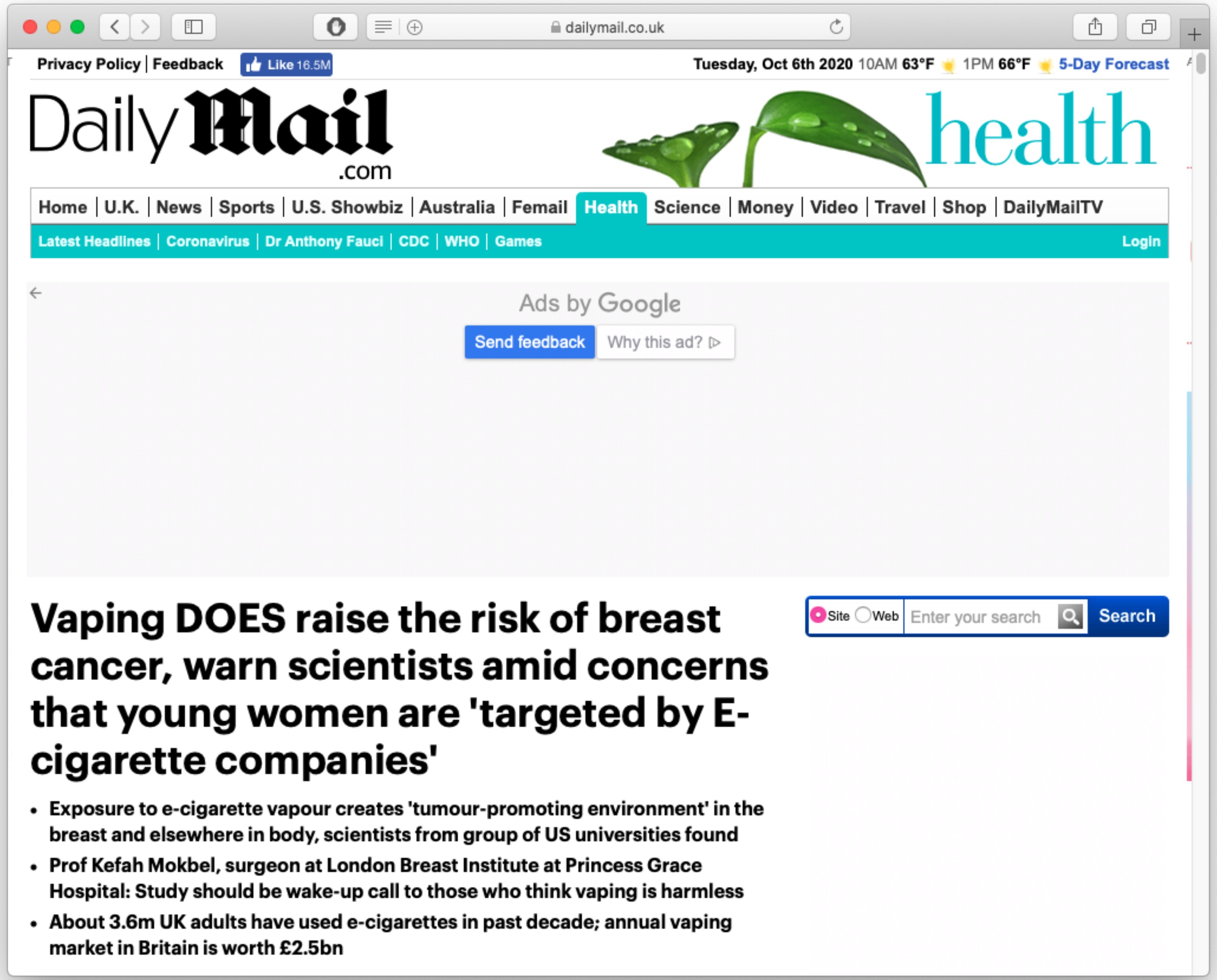
- Even if a study is **internally valid** (used statistics correctly, etc.) we must still worry about **external validity**:
- Is the finding **generalizable** to the whole population?
- If we find something in India, does that extend to Bolivia? France?
- Subjects of studies & surveys are often
  - **W**estern
  - **E**ducated
  - **I**ndustrialized
  - **R**ich
  - **D**emocracies

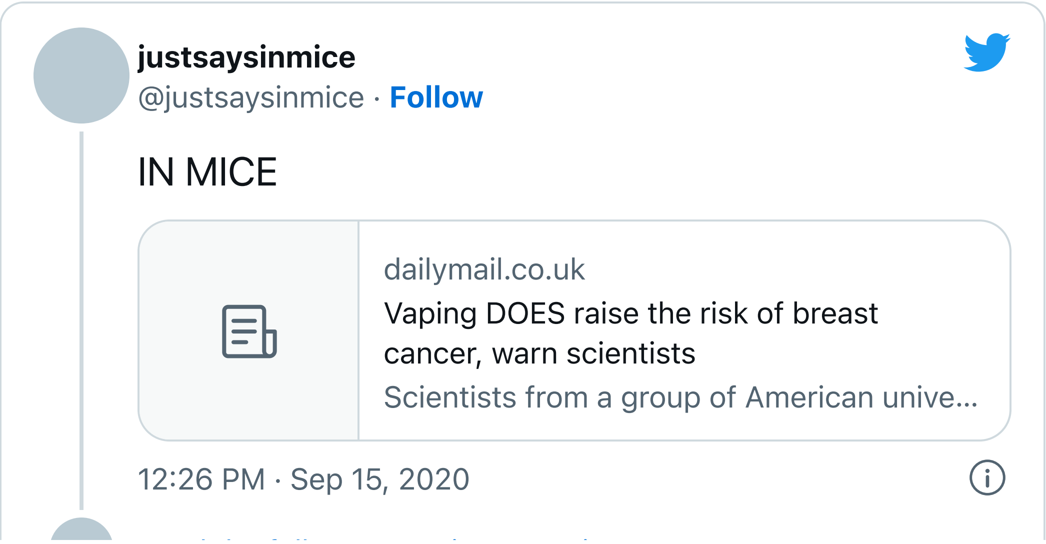
APA (2010)

RCTs and External Validity II



RCTs and External Validity II





In Mice twitter account