# Defining causal effects

UCLA SOCIOL 114: Social Data Science
Winter 2025

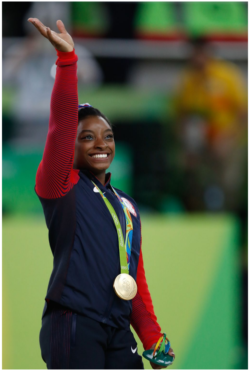
28 Jan 2025

# Learning goals for today

By the end of class, you will be able to

- explain the fundamental problem of causal inference and the need for causal arguments
- define potential outcomes
- recall mathematical concepts from probability
  - random variables
  - expectation
  - conditional expectation

# Causal claims hinge on arguments, not on data



Left photo: By Fernando Frazão/Agência Brasil - http://agenciabrasil.ebc.com.br/sites/_agenciabrasil2013/files/fotos/1035034-_mg_0802_04.08.16.jpg,CCBY3.0br,https://commons.wikimedia.org/w/index.php?curid=50548410
Right photo: By Agencia Brasil Fotografias - EUA levam ouro na ginástica artística feminina; Brasil fica em 8 lugar, CC BY 2.0, https://commons.wikimedia.org/w/index.php?curid=50584648

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| | Do you win gold if you: | | Causal effect |
|---|---|---|---|
| | Swing | Do not swing | of swinging |
| Simone Biles | Yes (1) | ? | ? |
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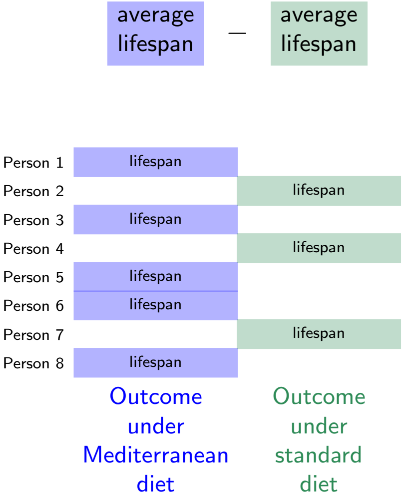
EXTRAVERGINE
olio
olio
olio

# Fundamental problem of causal inference

Holland 1986

## Descriptive evidence



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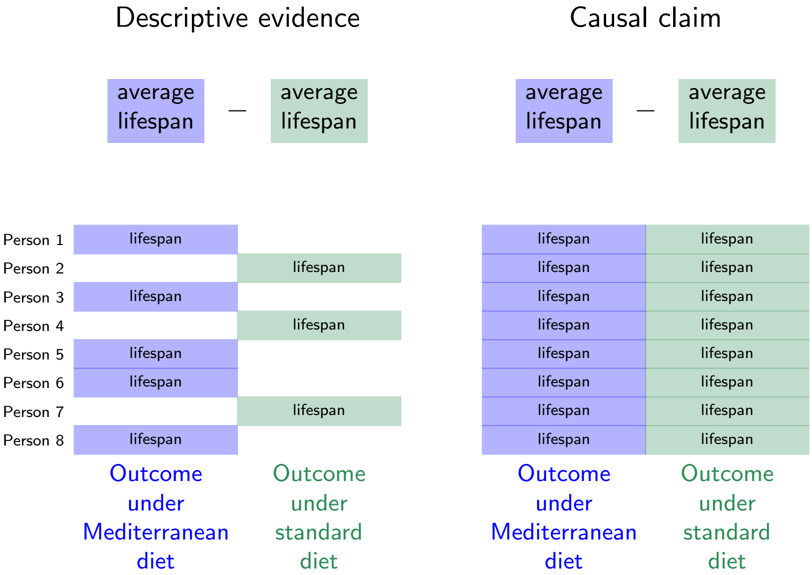

# Fundamental problem of causal inference

Holland 1986

## Descriptive evidence

average lifespan − average lifespan

| | | |
|---|---|---|
| Person 1 | lifespan | missing |
| Person 2 | missing | lifespan |
| Person 3 | lifespan | missing |
| Person 4 | missing | lifespan |
| Person 5 | lifespan | missing |
| Person 6 | lifespan | missing |
| Person 7 | missing | lifespan |
| Person 8 | lifespan | missing |

Outcome under Mediterranean diet | Outcome under standard diet

## Causal claim

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| | |
|---|---|
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## Causal claim

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## Causal inference is a **missing data** problem

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| $Y_{\text{Ian}}^{\text{MediterraneanDiet}} = \texttt{survived}$ | Ian would survive on a Mediterranean diet |

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**Discuss.**
Which potential outcome is observed?
Which is counterfactual?

# The consistency assumption

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$Y_i^{\text{MediterraneanDiet}}$

$Y_i^{\text{StandardDiet}}$

Potential Outcomes

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Factual Outcomes

# The consistency assumption

**Consistency Assumption**

$$Y_i^{A_i} = Y_i$$

$Y_i^{\text{MediterraneanDiet}}$

$Y_i^{\text{StandardDiet}}$

Potential Outcomes

$Y_i$

Factual Outcomes

# Mathematical notation: Potential outcomes are fixed

A person's potential outcome is a **fixed quantity**

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- The outcome $Y^{\text{MediterraneanDiet}}$ is a random variable:
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**Check for understanding:**
Does it make sense to write $\text{V}(Y_i^a)$? How about $\text{V}(Y^a)$

# Notation: Expectation operator

The **expectation operator** E() denotes the population mean

$$\mathrm{E}(Y^a) = \frac{1}{n}\sum_{i=1}^{n} Y_i^a$$

The quantity $Y^a$ inside the expectation must be a random variable

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A **conditional expectation** is denoted with a vertical bar

$$\text{E}(Y \mid A = a) = \frac{1}{n_a}\sum_{i:A_i=a} Y_i$$

# Practice: How would you say this in English?

We might wonder how a person's earnings relate to whether they hold a college degree

1. $\text{E}(\text{Earnings} \mid \text{Degree} = \texttt{TRUE}) > \text{E}(\text{Earnings} \mid \text{Degree} = \texttt{FALSE})$

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   - On average, a degree causes higher earnings

# Practice: How would you write this in math?

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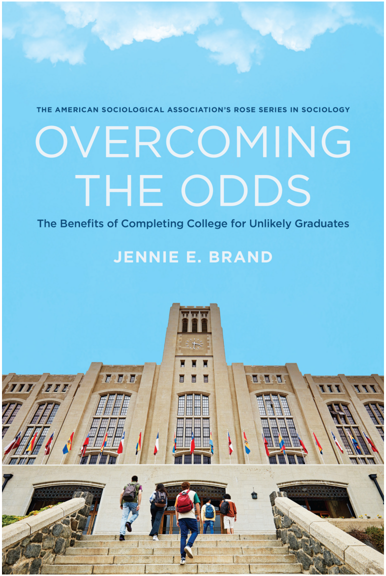
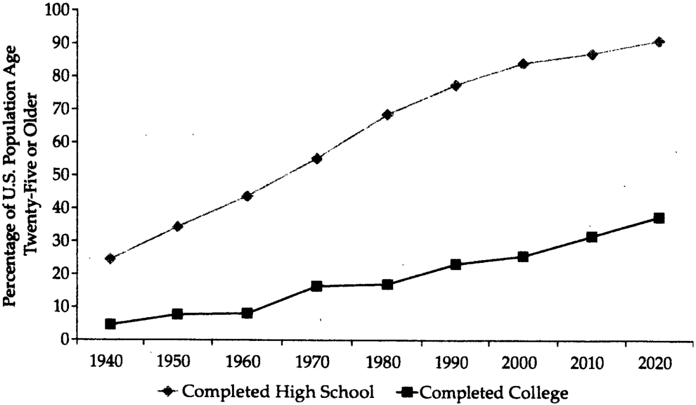
# An example about inequality



Americans' education in 1900 (Brand 2023 p. 6)

- 6% graduated from high school
- 3% graduated from college

**Figure 1.1 High School and Four-Year College Completion Rates, 1940–2020**




*Source:* U.S. Census Bureau, March Current Population Survey and Annual Social and Economic Supplement to the Current Population Survey.

(Brand 2023)

# Why did education expand?

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- Public investment in college
  - Morrill Act (1862) sold land to establish colleges
  - G.I. Bill (1944) funded veterans' college
- Rising labor market demand for skills

We would like to know whether **college pays off**:
does it have positive effects on desired outcomes?

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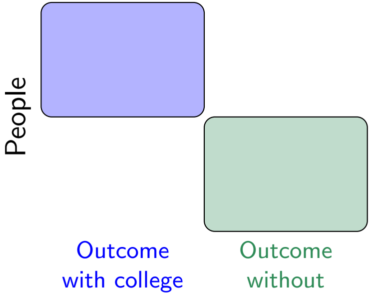

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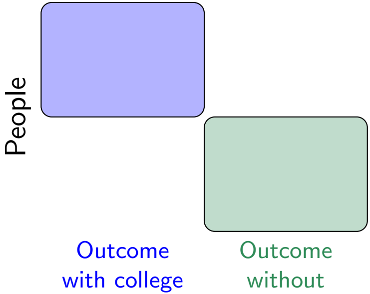

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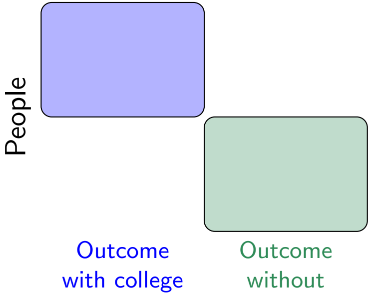


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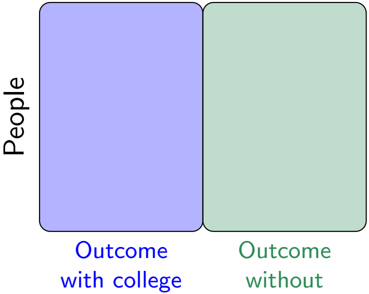

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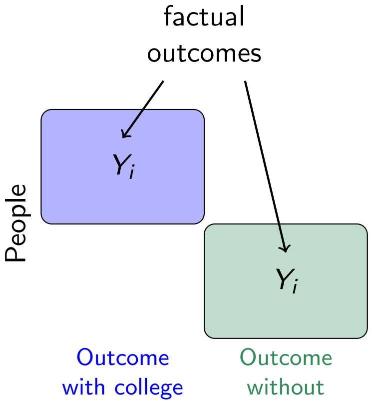


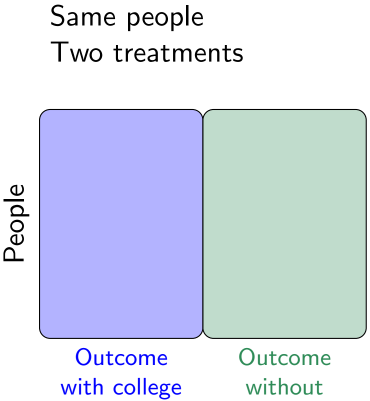

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People with college degrees earn more

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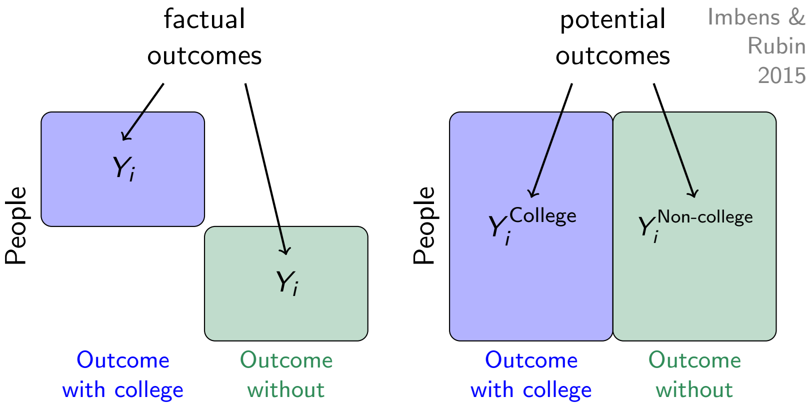

# The fundamental problem of causal inference

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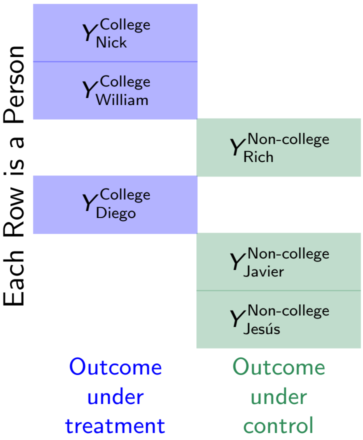


**Holland 1986**

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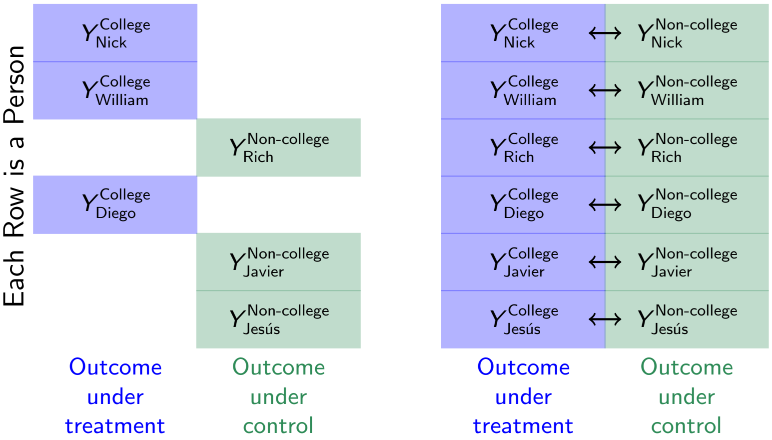


**Holland 1986**

# The fundamental problem of causal inference

Each Row is a Person

**The data**

| Outcome under treatment | Outcome under control |
|---|---|
| $Y^{\text{College}}_{\text{Nick}}$ | ? |
| $Y^{\text{College}}_{\text{William}}$ | ? |
| ? | $Y^{\text{Non-college}}_{\text{Rich}}$ |
| $Y^{\text{College}}_{\text{Diego}}$ | ? |
| ? | $Y^{\text{Non-college}}_{\text{Javier}}$ |
| ? | $Y^{\text{Non-college}}_{\text{Jesús}}$ |

**The claim**

| Outcome under treatment | | Outcome under control |
|---|---|---|
| $Y^{\text{College}}_{\text{Nick}}$ | $\longleftrightarrow$ | $Y^{\text{Non-college}}_{\text{Nick}}$ |
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Counterfactuals are **not observed**

**Holland 1986**

# Preview: Solving the problem by assumptions

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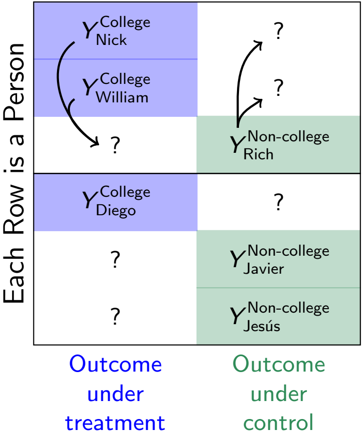
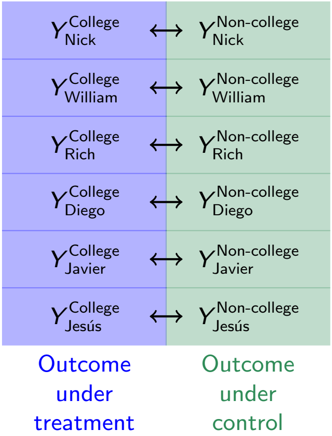
| $Y^{\text{College}}_{\text{Diego}}$ | $\longleftrightarrow$ | $Y^{\text{Non-college}}_{\text{Diego}}$ |
| $Y^{\text{College}}_{\text{Javier}}$ | $\longleftrightarrow$ | $Y^{\text{Non-college}}_{\text{Javier}}$ |
| $Y^{\text{College}}_{\text{Jesús}}$ | $\longleftrightarrow$ | $Y^{\text{Non-college}}_{\text{Jesús}}$ |

# Preview: Solving the problem by assumptions

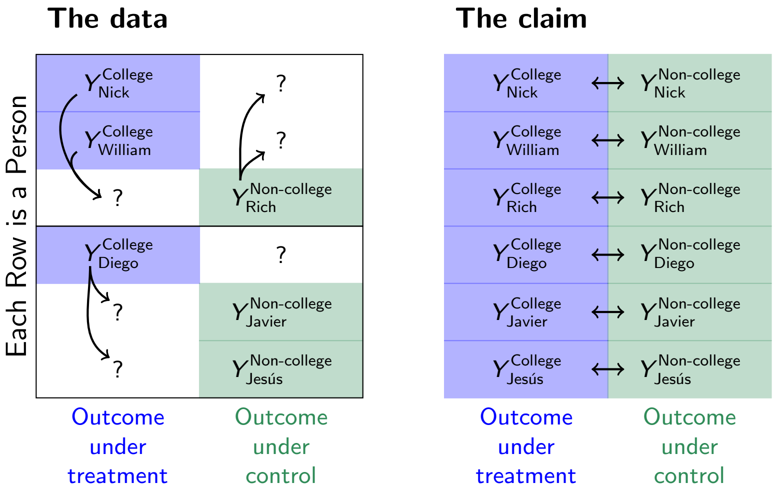
**The data**



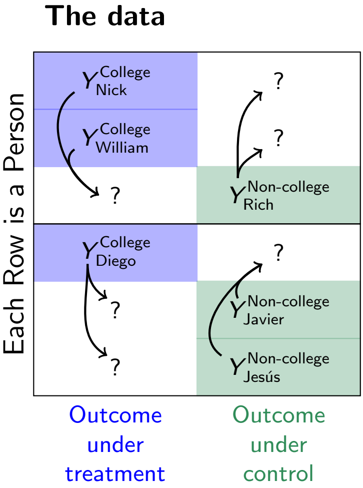

**The claim**

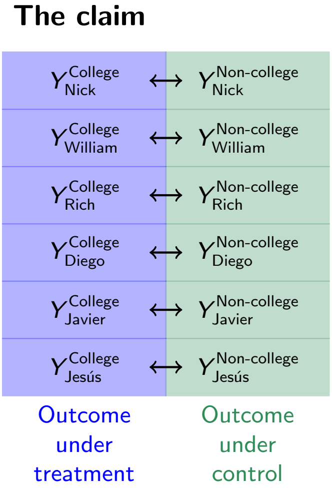


# Preview: Solving the problem by assumptions



# Preview: Solving the problem by assumptions



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   - Nick finished college college
   - outcome without college is unobserved
2. randomization solves the missing data problem by design
   - treated and control groups are exchangeable
3. observational studies solve the missing data problem by assumptions
   - find population subgroups who look similar before treatment
   - assume it is like an experiment within the subgroups

# Learning goals for today

By the end of class, you will be able to

- explain the fundamental problem of causal inference and the need for causal arguments
- define potential outcomes
- recall mathematical concepts from probability
  - random variables
  - expectation
  - conditional expectation

# You can now

- Read Chapter 1 of Hernán and Robins 2020