STA 235H - Potential Outcomes

Fall 2021

McCombs School of Business, UT Austin

Housekeeping

Homework 1 is due Thursday

- R review session is posted on Canvas.
- Remember to use the resources at your disposal: Office hours and Discussion Board.

Last week

- Finished our chapter on multiple regression.
    - Statistical Adjustment: Unveiling useful associations, interaction terms, multicollinearity.
- Residuals: Moved to week 8 (discrete responses in regression models).

Today

- Introduction to Causal Inference:

How? Potential Outcomes Framework

What? Causal Estimands

Why? Causal Questions and Study Design

The "How": Potential outcomes framework

Geoffrey Supran
@GeoffreySupran

"The @GretaThunberg Effect" is now an empirically demonstrated, peer-reviewed phenomenon:

"We find that those who are more familiar with Greta Thunberg have higher intentions of taking collective actions to reduce global warming."

Open access: onlinelibrary.wiley.com/doi/epdf/10.11...

Received: 5 December 2020 | Accepted: 18 December 2020
DOI: 10.1111/jasp.12737

ORIGINAL ARTICLE

Journal of Applied Social Psychology WILEY

The Greta Thunberg Effect: Familiarity with Greta Thunberg predicts intentions to engage in climate activism in the United States

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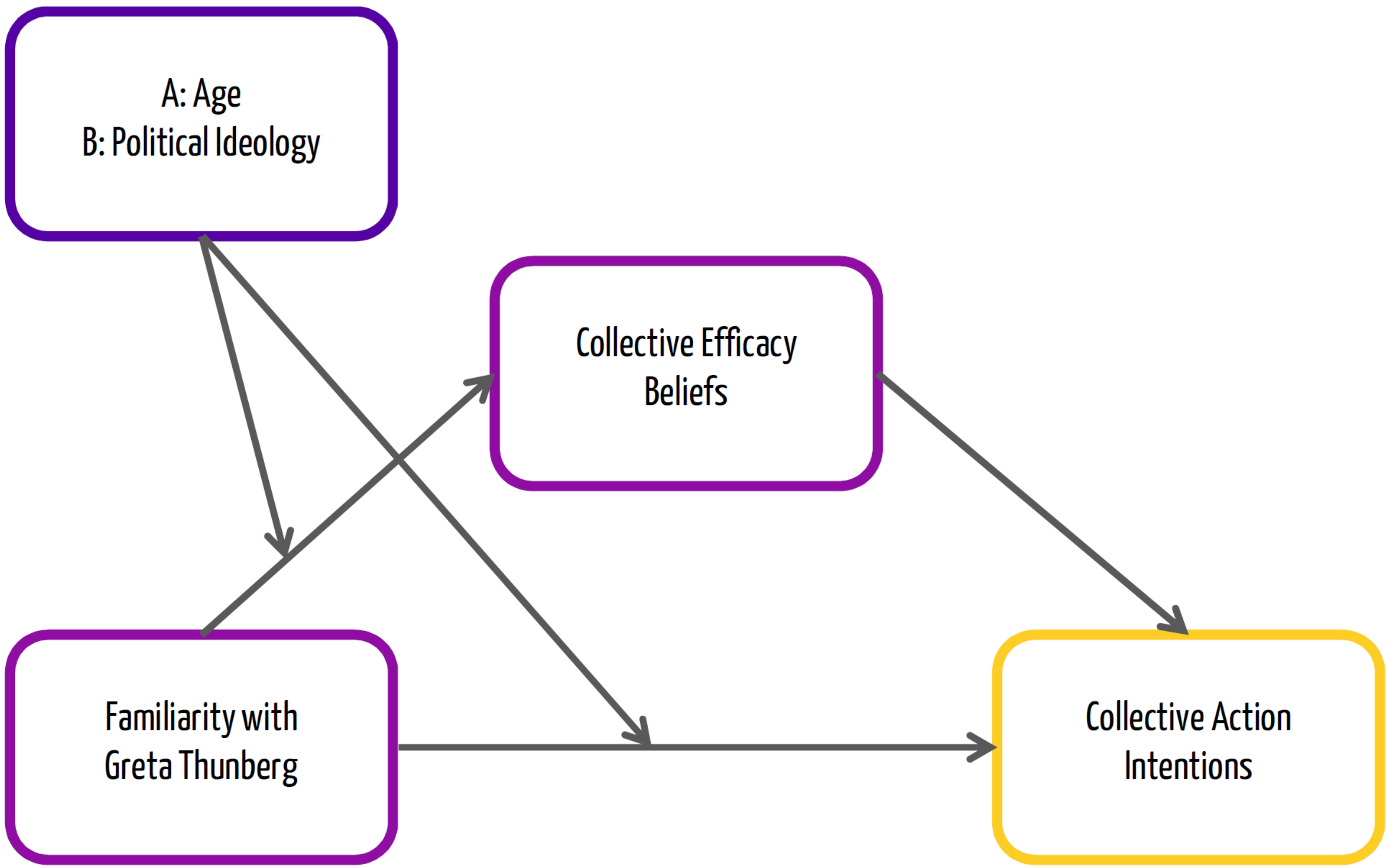
Abstract

Despite Greta Thunberg's popularity, research has yet to investigate her impact on the public's willingness to take collective action on climate change. Using cross-sectional data from a nationally representative survey of U.S. adults ($N = 1,303$), we investigate the "Greta Thunberg Effect," or whether exposure to Greta Thunberg predicts collective efficacy and intentions to engage in collective action. We find that those who are more familiar with Greta Thunberg have higher intentions of taking collective actions to reduce global warming and that stronger collective efficacy beliefs mediate this relationship. This association between familiarity with Greta Thunberg, collective ef-

the Year by some, and asked to “work on her anger management issues” by others (Alter et al., 2019; McCarthy, 2019). The present study, to date, is one of the first to present empirical evidence supporting the “Greta Thunberg Effect,” and to offer a potential explanation of why a young leader could be a powerful influence on collective action. We find that familiarity with Greta Thunberg is


A: Age
B: Political Ideology
Collective Efficacy Beliefs
Familiarity with Greta Thunberg
Collective Action Intentions

What do you think are the biggest issues here?

Khoa Vu
@KhoaVuUmn

"The Greta effect" Effect: Your misuse of causal language is never too wrong to make famous people retweet your study.

> **Hillary Clinton** @HillaryClinton · Jan 28
> Data proving @GretaThunberg right—"you are never too small to make a difference." twitter.com/GeoffreySupran...

11:22 AM · Jan 29, 2021 · Twitter Web App

What about other topics?

The Tesla Autosteer Case

OCTOBER 23, 2019

Tesla updates Autopilot safety numbers; almost 9x safer than average driving

Jameson Dow - Oct. 23rd 2019 5:50 pm ET

97 Comments | Facebook | Twitter | Pinterest | LinkedIn | Reddit

For more than a year now, Tesla has been releasing Autopilot safety numbers to show that autopilot is safer than a human driver in average driving conditions. In today's Tesla Q3 update, the company updated those numbers to show that autopilot is nearly 9x times safer than average driving.

There are caveats, of course. Autopilot is primarily used on highways, which have fewer accidents than surface streets because driving conditions are much simpler. And Teslas are generally newer cars, which are also less likely to be involved in accidents than the overall vehicle fleet, which includes old cars without modern active and passive safety features.

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SAFETY —

In 2017, the feds said Tesla Autopilot cut crashes 40%—that was bogus

Small firm gets Tesla crash data after 2-year legal battle with NHTSA, finds flawed study.

TIMOTHY B. LEE - 2/13/2019, 12:15 PM

Spencer Platt/Getty Images

Enlarge

The "Audi Effect"

> **Taras Grescoe**
> @grescoe
>
> STUDY: Drivers of luxury cars found to give pedestrians the right of way 3x less than those driving less expensive vehicles; 4x more likely to cut off other drivers.
>
> Call it the "Audi Effect."
> pic.twitter.com/2mlpWc2lkb
>
> 3,692 2:59 PM - Sep 8, 2021
>
> 1,298 people are talking about this

Before we start...

Be clear about your language

Before we start...

Be clear about your language

Be clear about your data

Before we start...

Be clear about your language

Be clear about your data

Be clear about your assumptions

What is Causal Inference?

Inferring the effect of one thing on another thing

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Inferring the effect of one thing on another thing

- "My headache went away because I took an aspirin".

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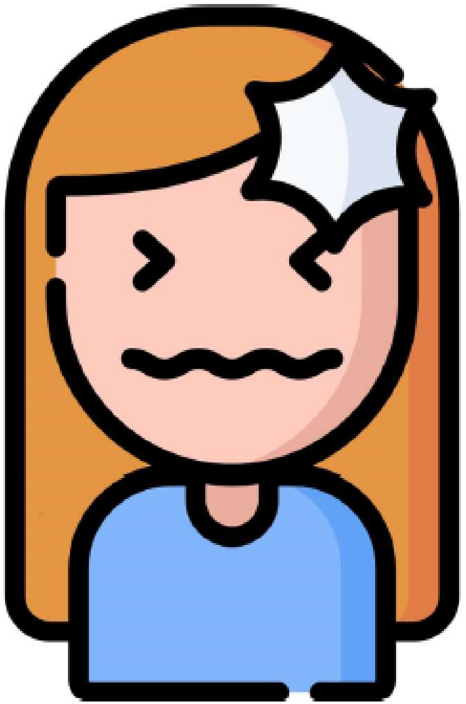
- "The new marketing campaign increased our sales by 20%"

What is Causal Inference?

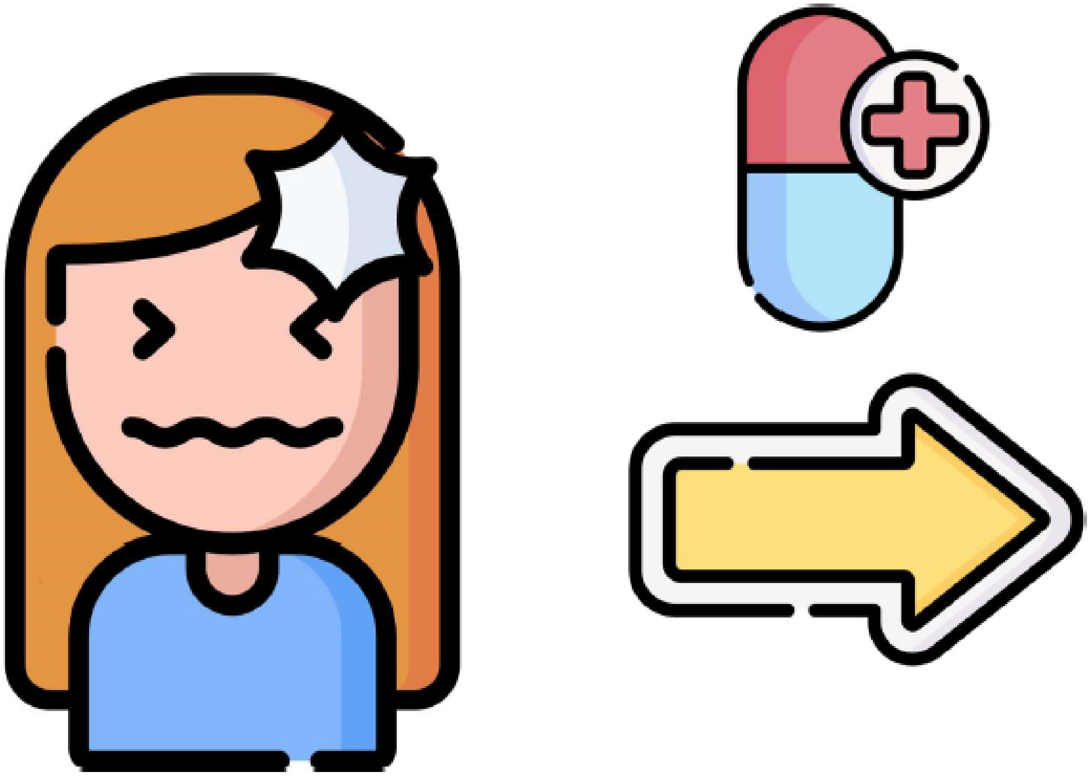
Inferring the effect of one thing on another thing

- "My headache went away because I took an aspirin".
- "The new marketing campaign increased our sales by 20%"
- "Providing students support when filling out FAFSA forms improves college access and completion."

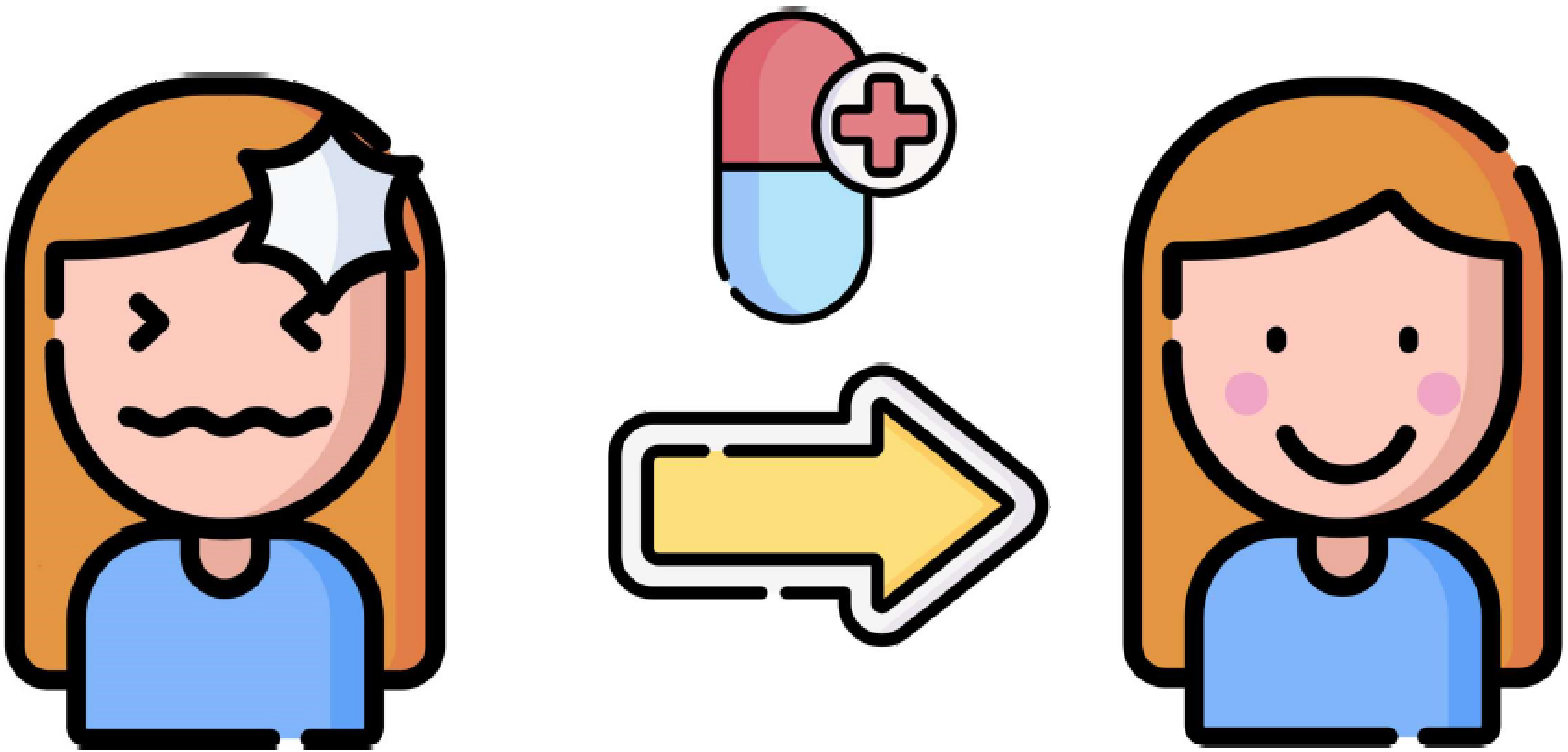
Imagine we have a headache...



A treatment could be an aspirin



Headache is gone!



Did the aspirin work?

Did the aspirin work?

We can't know!

A world of potential (outcomes)

- Under a binary treatment or intervention, there are **two potential worlds**:

A world of potential (outcomes)

- Under a binary treatment or intervention, there are **two potential worlds**:

- **World 1**: You take the pill
- **World 2**: You don't take the pill

A world of potential (outcomes)

- A **potential outcome** is the outcome under each of these scenarios or "worlds".
  - *There will be one for each path!*

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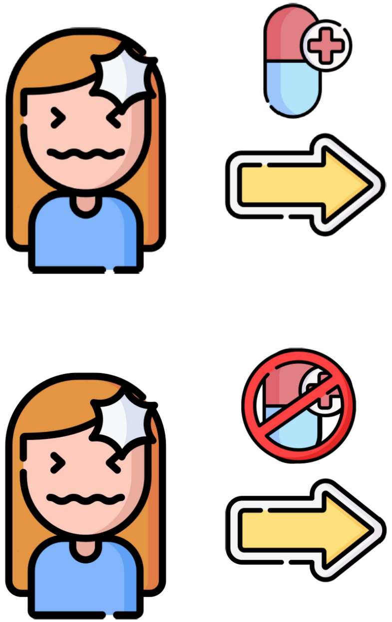
  - *There will be one for each path!*
- A priori, each of these scenarios has a *potential outcome*
- A posteriori, I can only observe **at most one of the potential outcomes**

Fundamental Problem of Causal Inference

What are the potential outcomes for our previous example?

Potential Outcomes: An example



Potential outcomes:

- Outcome if I take the pill
- Outcome if I don't take the pill

Potential Outcomes Framework

Let's introduce some notation:

- Let Y_i be the observed outcome for unit i (e.g. whether I have a headache or not in an hour).
- Let Z_i be the treatment or intervention (e.g. taking a pill).

Then,

$$Y_i|Z_i = 1 \triangleq Y_i(1)$$

where $Y_i(1)$ is the potential outcome under treatment.

In the same fashion,

$$Y_i|Z_i = 0 \triangleq Y_i(0)$$

where $Y_i(0)$ is the potential outcome under control.

Potential Outcomes Framework

This means that we can write the observed outcome as a function of the *potential outcomes*:

$$\rightarrow Y_i = Z_i \cdot Y_i(1) + (1 - Z_i) \cdot Y_i(0)$$

- This definition will be useful because we can see this as a **missing data problem**.

Causal Effects

Individual Causal Effect

$$ICE_i = Y_i(1) - Y_i(0)$$

Causal Effects

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Can we ever observe individual causal effects?

Causal Effects

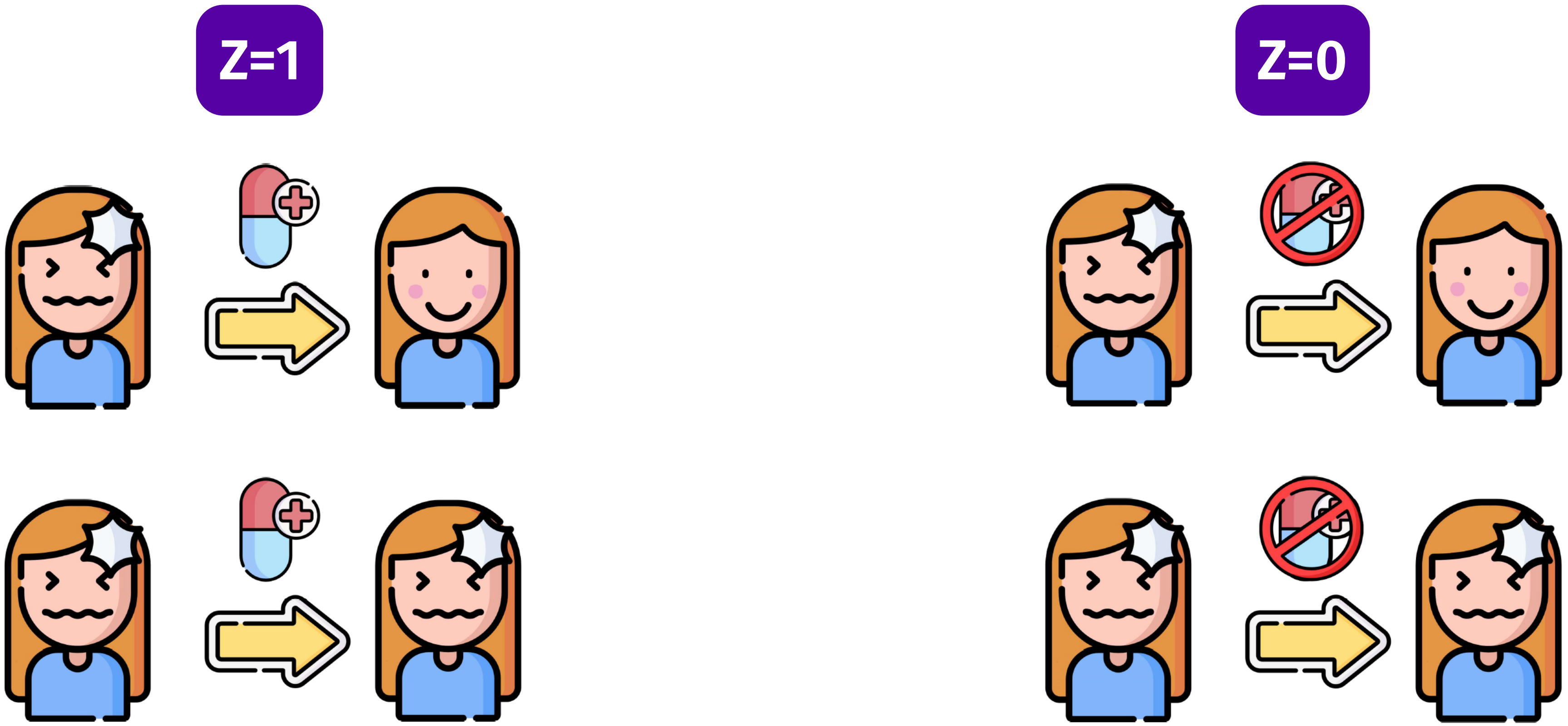
Individual Causal Effect

$$ICE_i = Y_i(1) - Y_i(0)$$

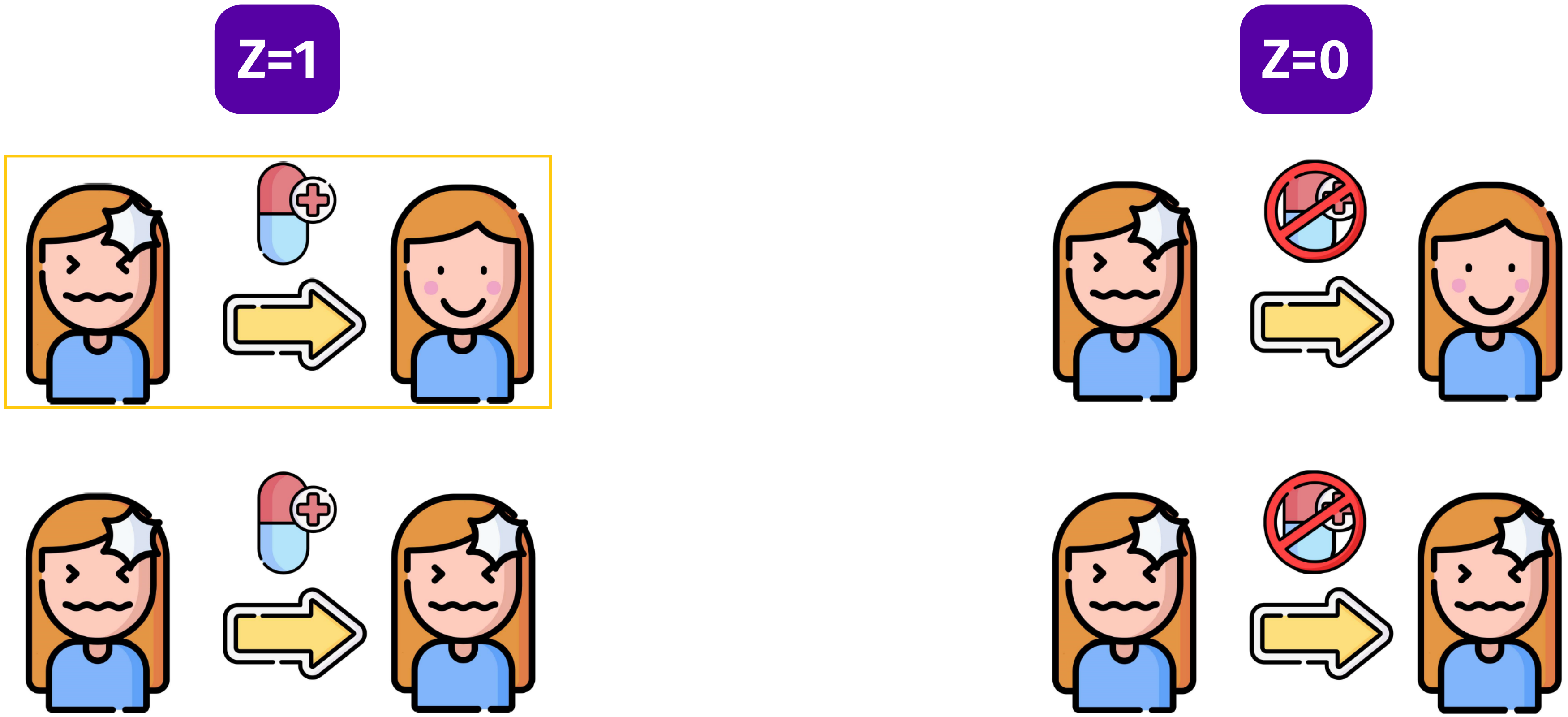
Can we ever observe individual causal effects?

No!*

Only one realization



Only one realization



The "What": Causal estimands, estimates, and estimators

Estimands vs Estimates vs Estimators

Estimand

A quantity we want to estimate

Estimator

A rule for calculating an estimate based on data

Estimate

The result of an estimation

Estimands vs Estimates vs Estimators

Estimand

A quantity we want to estimate

E.g.: Population mean

μ

Estimator

A rule for calculating an estimate based on data

E.g.: Sample mean

$$\frac{1}{n}\sum_i Y_i$$

Estimate

The result of an estimation

E.g.: Result of the sample mean for a given sample S

$\hat{\mu}$

Estimands vs Estimates vs Estimators

- Some important estimands that we need to keep in mind:

Average Treatment Effect (ATE)

Average Treatment Effect on the Treated (ATT)

Conditional Average Treatment Effect (CATE)

Estimands vs Estimates vs Estimators

- Some important **estimands** that we need to keep in mind:

$$ATE = E[Y(1) - Y(0)]$$

$$ATT = E[Y(1) - Y(0)|Z = 1]$$

$$CATE = E[Y(1) - Y(0)|X]$$

Getting around the fundamental problem of causal inference

- Let's go back to our original example: **Does a pill help reduce headaches?**

i	Z	Y	Y(1)	Y(0)	Y(1)-Y(0)
1	0	1	?	1	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	0	0	?	?

Getting around the fundamental problem of causal inference

- We have a **missing data problem**

i	Z	Y	Y(1)	Y(0)	Y(1)-Y(0)
1	0	1	?	1	?
2	1	1	1	?	?
3	1	0	0	?	?
4	0	0	?	0	?
5	0	1	?	1	?
6	1	0	0	?	?

Getting around the fundamental problem of causal inference

- Compare those who **took the pill** to the ones **did not take it.**

i	Z	Y	Y(1)	Y(0)	Y(1)-Y(0)
1	0	1	?	1	?
2	**1**	**1**	**1**	**?**	**?**
3	**1**	**0**	**0**	**?**	**?**
4	0	0	?	0	?
5	0	1	?	1	?
6	**1**	**0**	**0**	**?**	**?**

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$$\hat{\tau} = \frac{1}{3}\left(\sum_{i \in Z=1} Y_i - \sum_{i \in Z=0} Y_i\right) = -0.333$$

Getting around the fundamental problem of causal inference

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- What is the **estimand**?

Getting around the fundamental problem of causal inference

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Average Treatment Effect

Getting around the fundamental problem of causal inference

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Average Treatment Effect

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Difference in sample means

Getting around the fundamental problem of causal inference

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- What is the estimate and *how do we interpret it*?

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- What is the **estimand**?

Average Treatment Effect

- What is the **estimator**?

Difference in sample means

- What is the **estimate** and *how do we interpret it*?

33.3% decrease in probability of having a headache

The "Why": Causal questions and study designs

Under what assumptions is our estimate causal?

We are using:

$$\hat{\tau} = \frac{1}{3}(\sum_{i \in Z=1} Y_i - \sum_{i \in Z=0} Y_i)$$

to estimate:

$$\tau = E[Y_i(1) - Y_i(0)]$$

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Let's do some math

Under what assumptions is our estimate causal?

$$\tau = E[Y_i(1) - Y_i(0)]$$

$$= E[Y_i(1)] - E[Y_i(0)]$$

Key assumption:

Ignorability

- Ignorability means that the potential outcomes $Y(0)$ and $Y(1)$ are independent of the treatment, e.g. $(Y(0), Y(1)) \perp\!\!\!\perp Z$.

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  - *Remember that if* $A \perp\!\!\!\perp B \rightarrow E[A|B] = E[A]$

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$$\tau = E[Y_i(1)] - E[Y_i(0)] = \underbrace{E[Y_i(1)|Z=1]}_{\text{Obs. Outcome for T}} - \overbrace{E[Y_i(0)|Z=0]}^{\text{Obs. Outcome for C}}$$

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$$= E[Y_i|Z = 1] - E[Y_i|Z = 0]$$

Ignorability Assumption

We can just "ignore" the missing data problem:

i	Z	Y	Y(1)	Y(0)	Y(1)-Y(0)
1	0	1		1	
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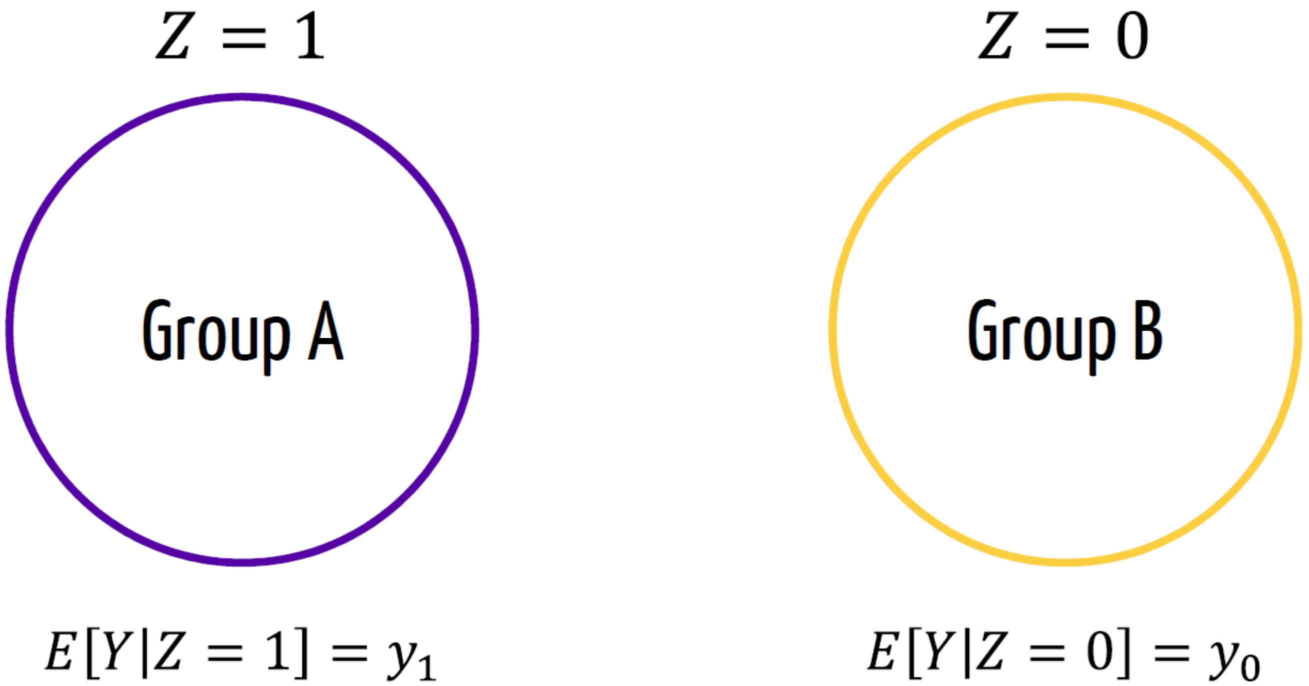
5	0	1		1	
6	1	0	0		
			1/3	2/3	

Ignorability Assumption

It's the same as the **exchangeability assumption**:



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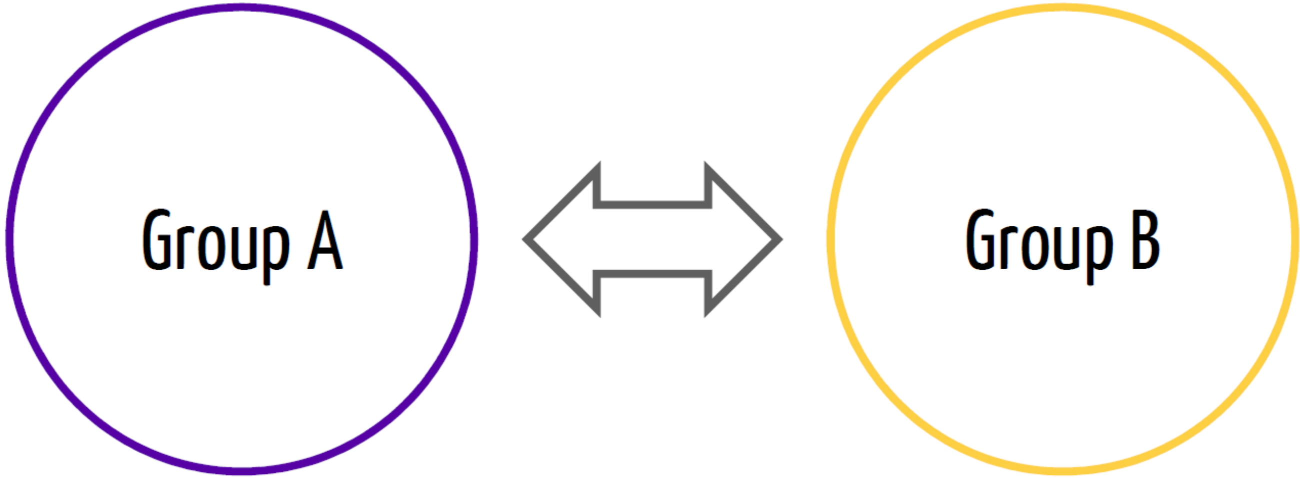

$Z = 1$ $\qquad$ $Z = 0$

$E[Y|Z = 1] = y_1$ $\qquad$ $E[Y|Z = 0] = y_0$

Ignorability Assumption

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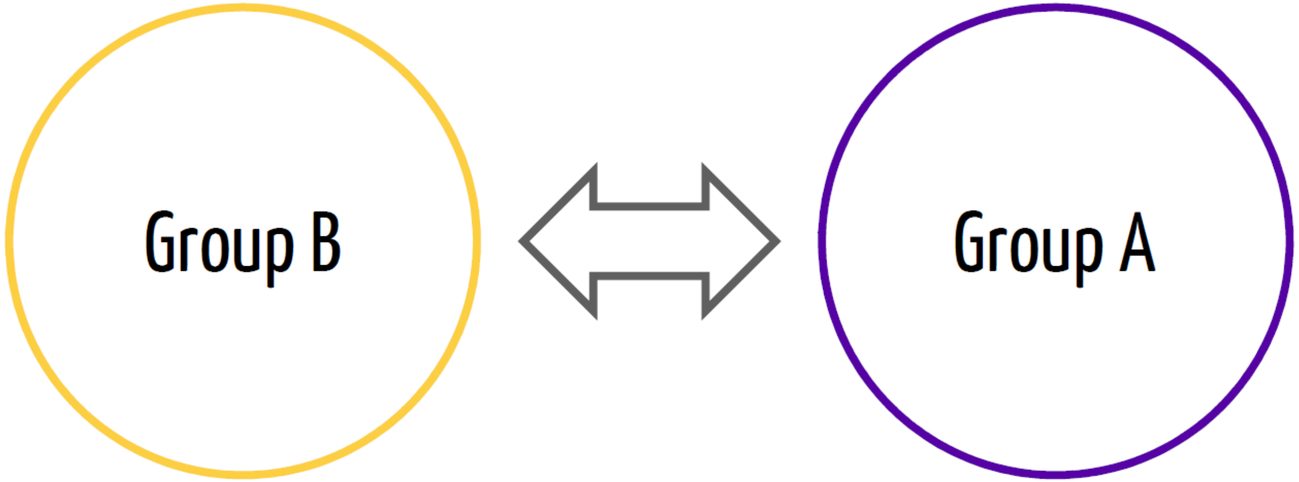

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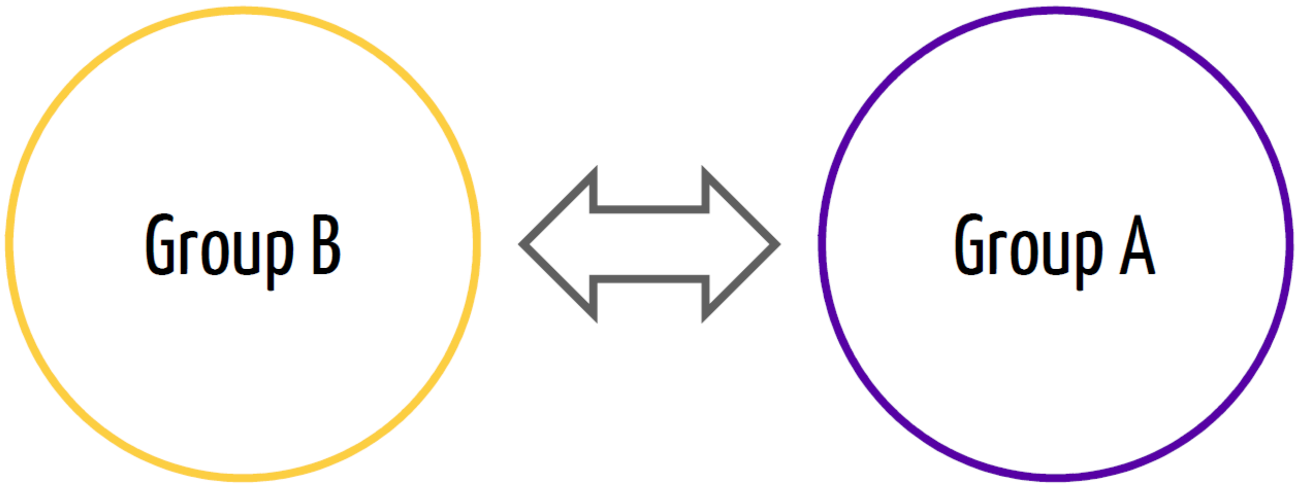

$E[Y|Z = 1] = y_1$ $\qquad$ $E[Y|Z = 0] = y_0$

$$E[Y(1)|Z = 1] = E[Y(1)|Z = 0] = E[Y(1)]$$

Ignorability Assumption

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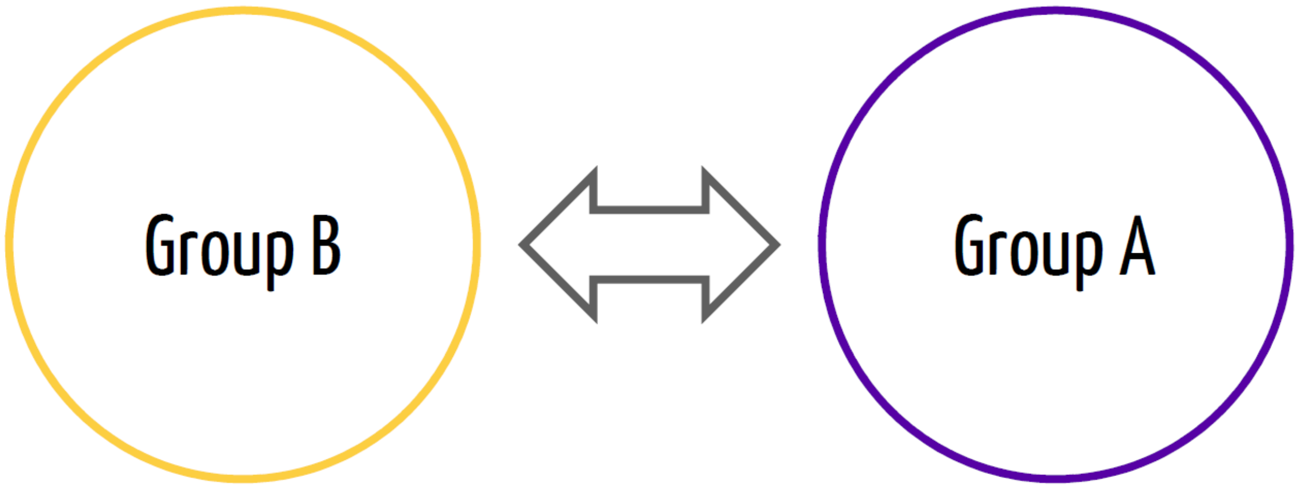

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$$E[Y(0)|Z = 1] = E[Y(0)|Z = 0] = E[Y(0)]$$

What happens if the ignorability assumption doesn't hold?

- Now, let's assume $(Y(0), Y(1)) \not\perp\!\!\!\perp Z$

$$\tau = E[Y_i(1)] - E[Y_i(0)] \neq E[Y_i | Z = 1] - E[Y_i | Z = 0]$$

Correlation does not imply causation

What happens if the ignorability assumption doesn't hold?

- Now, let's assume $(Y(0), Y(1)) \not\perp\!\!\!\perp Z$

$$\tau = E[Y_i(1) - Y_i(0)] =$$

$$= E[Y_i(1) - Y_i(0)|Z = 1]Pr(Z = 1) + E[Y_i(1) - Y_i(0)|Z = 1](1 - Pr(Z = 1))$$

What happens if the ignorability assumption doesn't hold?

- Now, let's assume $(Y(0), Y(1)) \not\perp\!\!\!\perp Z$

$$\tau = E[Y_i(1) - Y_i(0)] =$$

$$= \underbrace{E[Y_i(1) - Y_i(0)|Z = 1]}_{\text{ATT}} Pr(Z = 1) + \overbrace{E[Y_i(1) - Y_i(0)|Z = 0]}^{\text{ATC}} (1 - Pr(Z = 1))$$

- Weighted average of the ATT and ATC.

What happens if the ignorability assumption doesn't hold?

- After some simple math, you can get to:

$$\tau = E[Y_i(1) - Y_i(0)] = ATE$$

$$\begin{aligned} ATE = E[Y_i|Z=1] - E[Y_i|Z=0] \\ - (E[Y_i(0)|Z=1] - E[Y_i(0)|Z=0]) \\ - (1 - Pr(Z=1))(ATT - ATC) \end{aligned}$$

Check out Scott Cunningham's "Causal Inference: The Mixtape" (Ch. 4.1.3) for the decomposition

What happens if the ignorability assumption doesn't hold?

- After some simple math, you can get to:

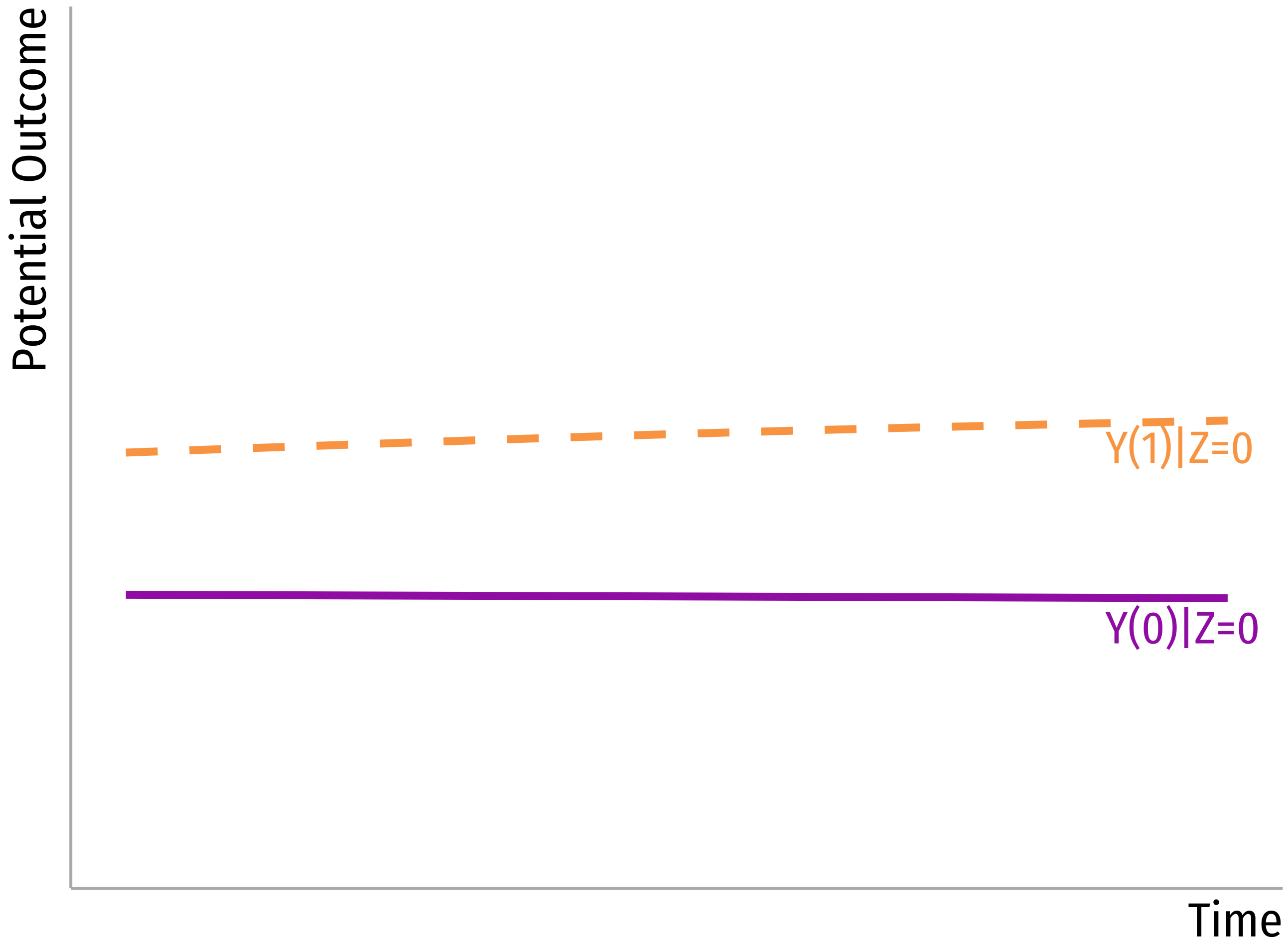
$$\tau = E[Y_i(1) - Y_i(0)] = ATE$$

$$\begin{aligned} ATE = & \underbrace{E[Y_i|Z=1] - E[Y_i|Z=0]}_{\text{Obs diff in means}} \\ & - \underbrace{(E[Y_i(0)|Z=1] - E[Y_i(0)|Z=0])}_{\text{Selection bias}} \\ & - \underbrace{(1 - Pr(Z=1))(ATT - ATC)}_{\text{Heterogeneous treat. effect bias}} \end{aligned}$$

- **Selection Bias:** Difference between groups if they both were under control.
- **Heterogeneous Treatment Effect Bias:** Difference in returns to treatment for the two groups (weighted by the control population).

Check out Scott Cunningham's "Causal Inference: The Mixtape" (Ch. 4.1.3) for the decomposition

How would bias look like?



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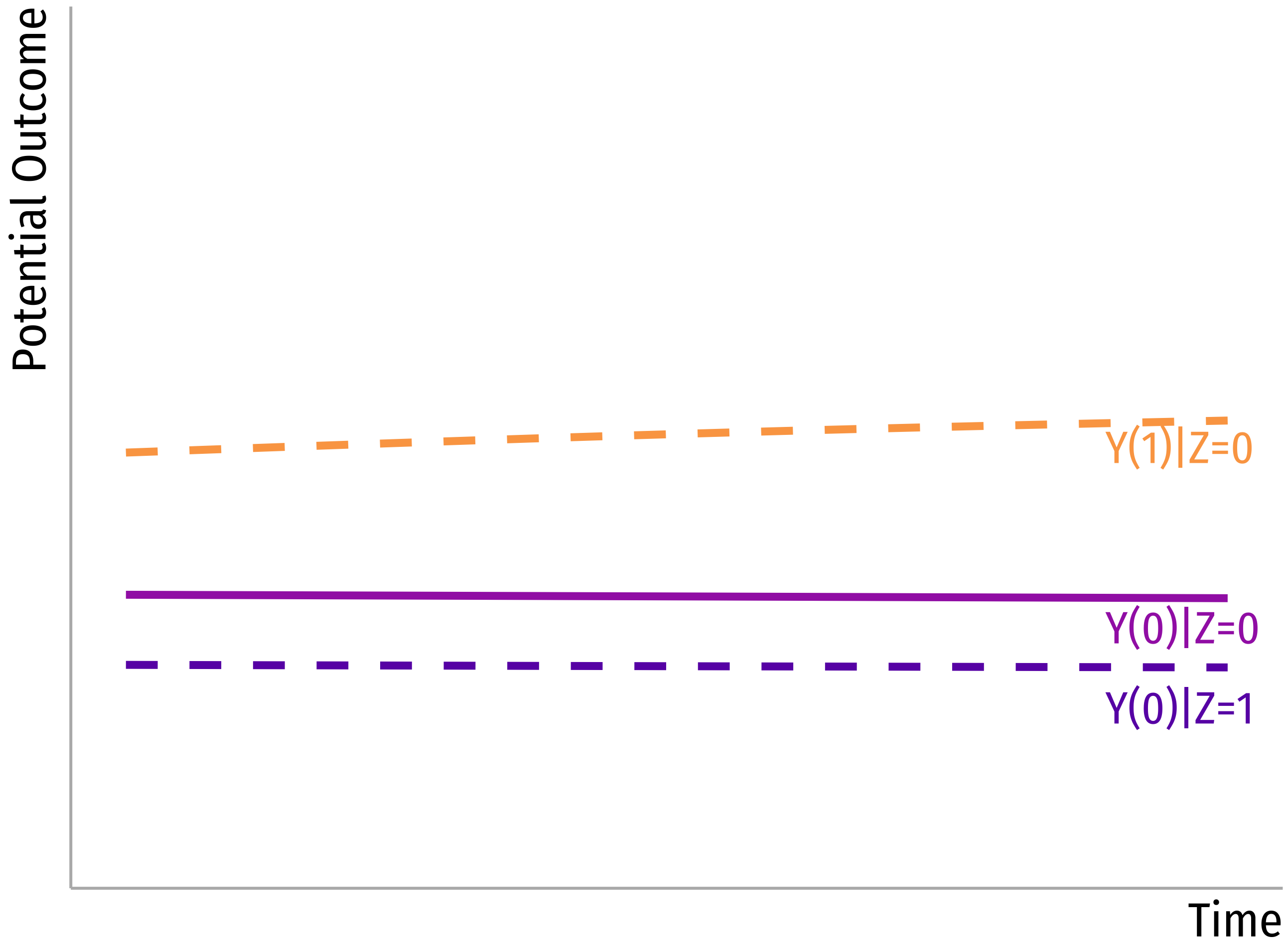

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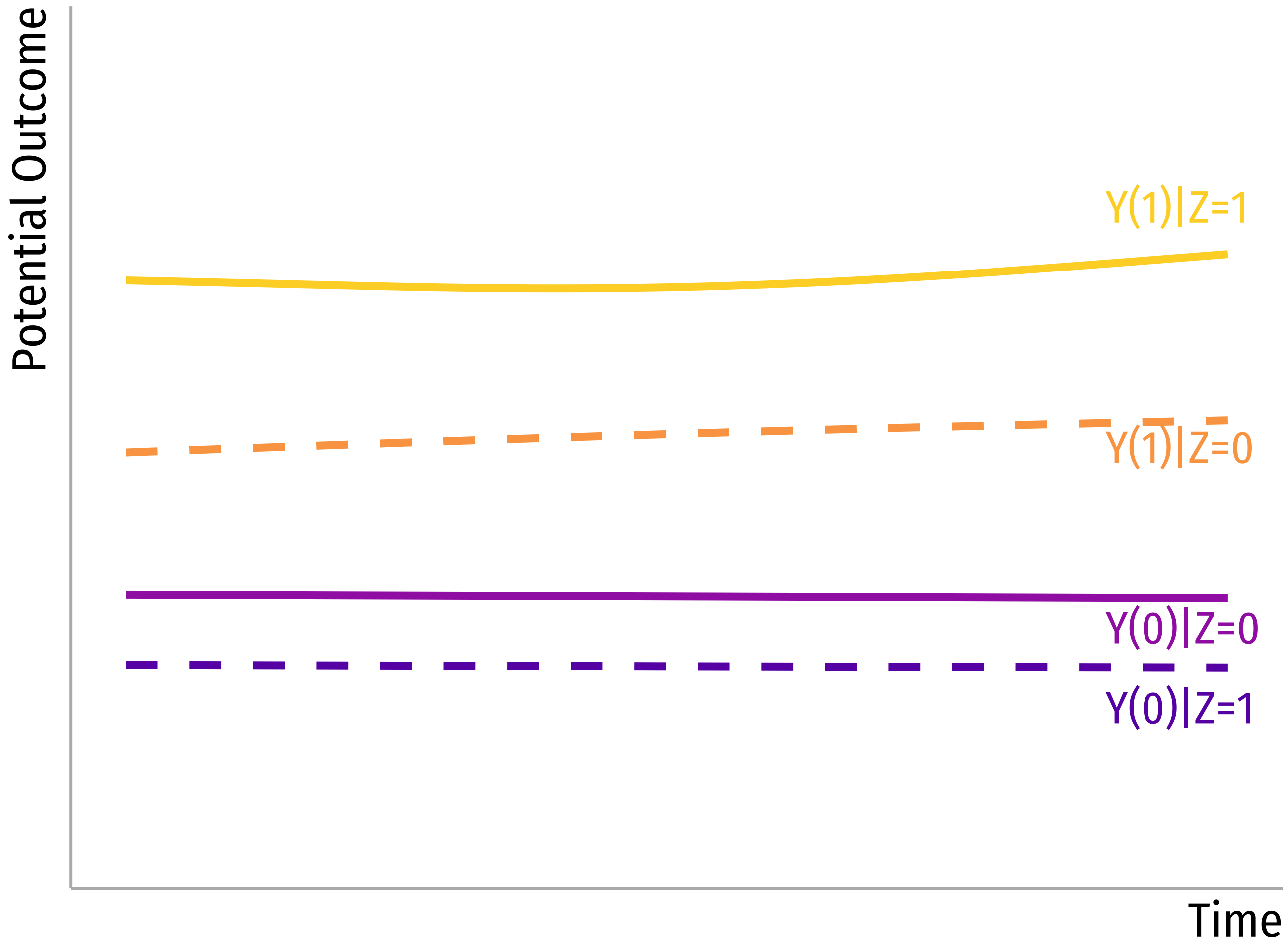

Let's look at some data

Example: Effect of types of advertising on sales

You want to know whether is more convenient to e-mail or physically mail potential customers to increase your sales.

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- What is the **treatment**?

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You want to know whether is more convenient to **e-mail** or **physically mail** potential customers to increase your sales.

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- What is the **causal question** that you want to answer?

Example: Effect of types of advertising on sales

You want to know whether is more convenient to e-mail or physically mail potential customers to increase your sales.

- What is the treatment?
- What is the causal question that you want to answer?
- What would the counterfactual be?

Looking at some data

- You get some data from a friend in Silicon Valley, who works at a similar company:

% of New Registrations by Type of Campaign

Treatment	Total
E-mail	19%
	(290/1500)
Mail	16%
	(88/550)

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Does this mean that e-mailing is more effective in getting new customers?

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	(290/1500)
Mail	16%
	(88/550)

Does this mean that e-mailing is more effective in getting new customers?

What additional information would you need?

Let's add some covariates

- Your friend now also sends you additional data on whether the individual had ever visited the site:

% of New Registrations by Type of Campaign and Visits to the Website

Treatment	Visited web	Not visited web	Total
E-mail	10%	20%	19%
	10/100	280/1400	(290/1500)
Mail	15%	31%	16%
	77/514	11/36	(88/550)

What seems strange?

Let's add some covariates

- The majority of the sample that was assigned to "E-mail" had not visited the website before, while the majority of the sample that was sent a mailing had visited the website.

% of the Sample in each Category by Site Visit

Treatment	Visited web	Not visited web
E-mail	6.7%	93.4%
Mail	93.4%	6.5%

Let's add some covariates

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	10/100	280/1400	(290/1500)
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	77/514	11/36	(88/550)

Do we have a confounding problem?

Confounding

Confounder

Variable that is correlated with the treatment AND the outcome which causes a spurious correlation/bias.

Is "Visited the website" a confounder?

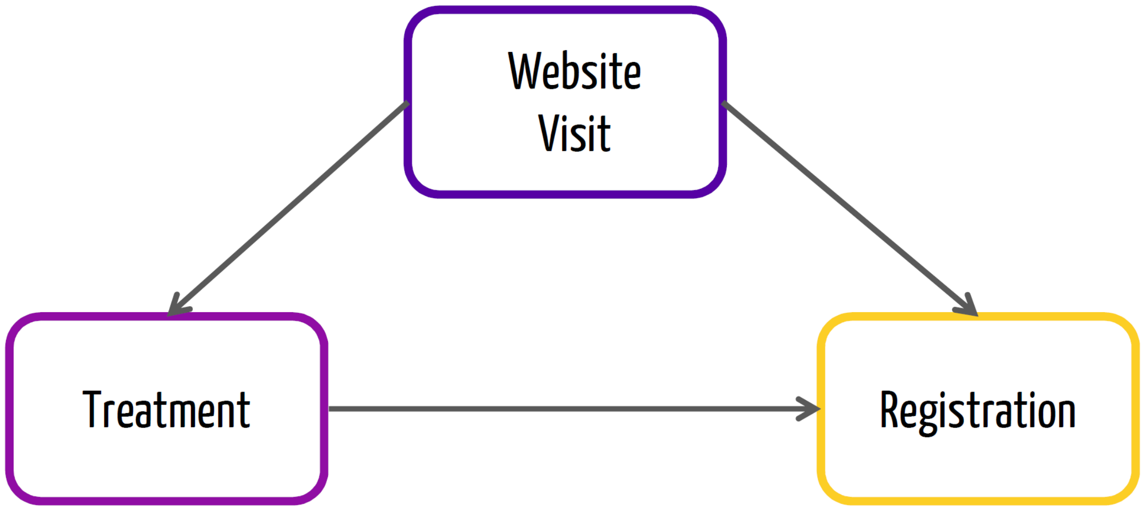
Is "Visited the website" a confounder?

Depends

- **Measured before the intervention:** Yes → Individuals that have **not** visited the website (VW) don't know you/ might be more willing to try product.
- **Measured after the intervention:** Don't know → Intervention might have incentivized people to go to the website, and registering also had on effect on traffic.

Collider

Scenario 1: Confounding



Scenario 1: Confounding

Data Generating Process:

- No treatment effect.
- Pr(Registering | Visit) < Pr(Registering | Not Visited)
- Due to data collection, more people in the mailing sample had visited the website than people in the email sample.

Num in Sample and % of New Registrations by Type of Campaign and Visits to the Website

	Not visited	Visited	Registered - NV	Registered - V	Registered - Total
Email	1404	91	0.22	0.12	0.21
Mail	32	523	0.28	0.15	0.15

Note: Simulated data

Scenario 1: Confounding

What happens if we run a simple model?

```
summary(lm(y ~ factor(treat), data = confound))
```

- What would you expect to see?

Scenario 1: Confounding

What happens if we run a simple model?

```r
summary(lm(y ~ factor(treat), data = confound))
```

```
##
## Call:
## lm(formula = y ~ factor(treat), data = confound)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2107 -0.2107 -0.2107 -0.1532  0.8468
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.21070    0.01023  20.590  < 2e-16 ***
## factor(treat)m -0.05755    0.01967  -2.926  0.00347 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3957 on 2048 degrees of freedom
## Multiple R-squared:  0.004164,    Adjusted R-squared:  0.003677
## F-statistic: 8.563 on 1 and 2048 DF,  p-value: 0.003469
```

Scenario 1: Confounding

What happens if we now control by whether the person visited the website?

```
summary(lm(y ~ factor(treat) + visit, data = confound))
```

Scenario 1: Confounding

What happens if we now **control by whether the person visited the website**?

```r
summary(lm(y ~ factor(treat) + visit, data = confound))
```

```
##
## Call:
## lm(formula = y ~ factor(treat) + visit, data = confound)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2532 -0.2172 -0.2172 -0.1470  0.8890
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.21716    0.01046  20.768  < 2e-16 ***
## factor(treat)m  0.03602    0.03786   0.951  0.34154
## visit           -0.10615    0.03673  -2.890  0.00389 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.395 on 2047 degrees of freedom
## Multiple R-squared:  0.00821,    Adjusted R-squared:  0.007241
## F-statistic: 8.473 on 2 and 2047 DF,  p-value: 0.0002165
```

Scenario 1: Confounding

What happens if we now **control by whether the person visited the website**?

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summary(lm(y ~ factor(treat) + visit, data = confound))
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```
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## -0.2532 -0.2172 -0.2172 -0.1470  0.8890
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##                 Estimate Std. Error t value Pr(>|t|)
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## factor(treat)m   0.03602    0.03786   0.951  0.34154
## visit           -0.10615    0.03673  -2.890  0.00389 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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## Multiple R-squared:  0.00821,    Adjusted R-squared:  0.007241
## F-statistic: 8.473 on 2 and 2047 DF,  p-value: 0.0002165
```
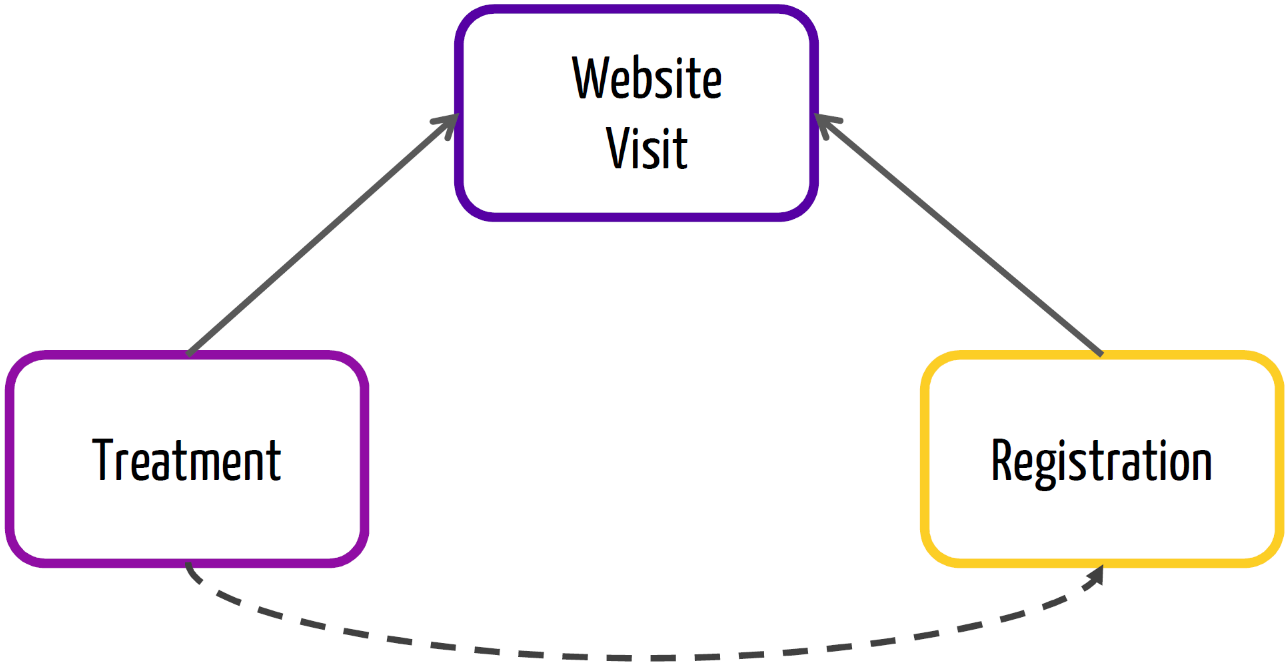

- **What conclusions would you make?**

Scenario 2: Collider Bias



Scenario 2: Collider Bias

Data Generating Process:

- No direct treatment effect of mailing over emails.
- Pr(Visit | e-mail) < Pr(Visit | mail)
- People that receive a letter are much more encouraged to visit the website, and people that register are also more likely to visit the website.

Num in Sample and % of New Registrations by Type of Campaign and Visits to the Website

	Not visited	Visited	Registered - NV	Registered - V	Registered - Total
Email	1409	94	0.19	0.11	0.18
Mail	45	502	0.31	0.15	0.16

Note: Simulated data

Scenario 2: Collider Bias

What happens if we now **run a simple model**?

```
summary(lm(y ~ factor(treat), data = collider))
```

- what would you **expect** to see?

Scenario 2: Collider Bias

What happens if we now **run a simple model**?

```r
summary(lm(y ~ factor(treat), data = collider))
```

```
##
## Call:
## lm(formula = y ~ factor(treat), data = collider)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.1843 -0.1843 -0.1843 -0.1627  0.8373
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.18430    0.00988  18.654   <2e-16 ***
## factor(treat)m -0.02159    0.01913  -1.129    0.259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.383 on 2048 degrees of freedom
## Multiple R-squared:  0.0006219,	Adjusted R-squared:  0.0001339
## F-statistic: 1.274 on 1 and 2048 DF,  p-value: 0.2591
```

Scenario 2: Collider Bias

What happens if we now **control by whether the person visited the website**?

```
summary(lm(y ~ factor(treat) + visit, data = collider))
```

Scenario 2: Collider Bias

What happens if we now **control by whether the person visited the website**?

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summary(lm(y ~ factor(treat) + visit, data = collider))
```

```
##
## Call:
## lm(formula = y ~ factor(treat) + visit, data = collider)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2620 -0.1911 -0.1911 -0.1538  0.9171
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.19106    0.01008  18.957   <2e-16 ***
## factor(treat)m   0.07093    0.03449   2.057   0.0398 *
## visit           -0.10819    0.03359  -3.221   0.0013 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3822 on 2047 degrees of freedom
## Multiple R-squared:  0.005661,    Adjusted R-squared:  0.004689
## F-statistic: 5.827 on 2 and 2047 DF,  p-value: 0.002997
```

Scenario 2: Collider Bias

What happens if we now **control by whether the person visited the website**?

```r
summary(lm(y ~ factor(treat) + visit, data = collider))
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```
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## Call:
## lm(formula = y ~ factor(treat) + visit, data = collider)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.2620 -0.1911 -0.1911 -0.1538  0.9171
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## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.19106    0.01008  18.957   <2e-16 ***
## factor(treat)m    0.07093    0.03449   2.057   0.0398 *
## visit            -0.10819    0.03359  -3.221   0.0013 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3822 on 2047 degrees of freedom
## Multiple R-squared:  0.005661,    Adjusted R-squared:  0.004689
## F-statistic: 5.827 on 2 and 2047 DF,  p-value: 0.002997
```

What happened here?

Avoiding biases in Causal Inference

- Always check your data!

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- Assess the plausibility of the ignorability assumption

Avoiding biases in Causal Inference

- Always check your data!
- Assess the plausibility of the ignorability assumption
- The model you have in your head matters!

Avoiding biases in Causal Inference

- Always check your data!
- Assess the plausibility of the ignorability assumption
- The model you have in your head matters!
- Avoid controlling for ex-post variables.

Another Example: Beauty in the Classroom

- Data: Student's evaluations for instructors at UT Austin

```r
profs <- read.csv("https://raw.githubusercontent.com/maibennett/sta235/main/exampleSite/content/Classes/Week3/2_PotentialC
                  stringsAsFactors = TRUE)

head(profs)
```

```
##   minority age gender credits     beauty eval division native tenure students
## 1      yes  36 female    more  0.2899157  4.3    upper    yes    yes       24
## 2       no  59   male    more -0.7377322  4.5    upper    yes    yes       17
## 3       no  51   male    more -0.5719836  3.7    upper    yes    yes       55
## 4       no  40 female    more -0.6779634  4.3    upper    yes    yes       40
## 5       no  31 female    more  1.5097940  4.4    upper    yes    yes       42
## 6       no  62   male    more  0.5885687  4.2    upper    yes    yes      182
##   allstudents prof
## 1          43    1
## 2          20    2
## 3          55    3
## 4          46    4
## 5          48    5
## 6         282    6
```

Beauty and Evaluations

- **Causal Question:** What is the effect of beauty on teachers evaluations?

Beauty and Evaluations

- **Causal Question:** What is the effect of beauty on teachers evaluations?

```
summary(lm(eval ~ beauty, data=profs))
```

```
##
## Call:
## lm(formula = eval ~ beauty, data = profs)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.80015 -0.36304  0.07254  0.40207  1.10373
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.99827    0.02535 157.727  < 2e-16 ***
## beauty       0.13300    0.03218   4.133 4.25e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5455 on 461 degrees of freedom
## Multiple R-squared:  0.03574,    Adjusted R-squared:  0.03364
## F-statistic: 17.08 on 1 and 461 DF,  p-value: 4.247e-05
```

Clearly not causal

Beauty and Evaluations

- **Causal Question:** What is the effect of beauty on teachers evaluations?
- What **other things** could be biasing our estimate?
    - Distinction between what's in our data vs what it's not.

Let's check our data

- Simplify the problem:
  - **Binary Treatment**: Beauty above average (1) vs Below average (0)

```r
profs <- profs %>% mutate(treat = as.numeric(beauty > 0),
                          female = 2 - as.numeric(gender),
                          single_credit = as.numeric(credits)-1,
                          upper_div = as.numeric(division)-1,
                          native = as.numeric(native)-1,
                          tenure = as.numeric(tenure)-1,
                          minority = as.numeric(minority)-1)
```

Let's check our data

- Simplify the problem:
  - **Binary Treatment**: Beauty above average (1) vs Below average (0)

```
profs <- profs %>% mutate(treat = as.numeric(beauty > 0),
                          female = 2 - as.numeric(gender),
                          single_credit = as.numeric(credits)-1,
                          upper_div = as.numeric(division)-1,
                          native = as.numeric(native)-1,
                          tenure = as.numeric(tenure)-1,
                          minority = as.numeric(minority)-1)

library(modelsummary)

covs <- profs %>% select(treat, minority, age, female, single_credit, upper_div,
         native, tenure, students, allstudents)

datasummary_balance(~ treat, data = covs, title = "Balance table", fmt=2, dinm_statistic = "p.value")
```

Let's check our data

- Simplify the problem:
  - Binary Treatment: Beauty above average (1) vs Below average (0)

```
profs <- profs %>% mutate(treat = as.numeric(beauty > 0),
                          female = 2 - as.numeric(gender),
                          single_credit = as.numeric(credits)-1,
                          upper_div = as.numeric(division)-1,
                          native = as.numeric(native)-1,
                          tenure = as.numeric(tenure)-1,
                          minority = as.numeric(minority)-1)

library(modelsummary)

covs <- profs %>% select(treat, minority, age, female, single_credit, upper_div,
         native, tenure, students, allstudents)

datasummary_balance(~ treat, data = covs, title = "Balance table", fmt=2, dinm_statistic = "p.value")
```

Let's check our data

```r
datasummary_balance(~ treat, data = covs, title = "Balance table", fmt=2, dinm_statistic = "p.value")
```

Balance table

	0		1			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
minority	-1.88	0.33	-1.84	0.37	0.04	0.27
age	50.56	9.44	45.12	9.44	-5.44	0.00
female	0.37	0.48	0.50	0.50	0.13	0.01
single_credit	0.08	0.27	0.03	0.16	-0.05	0.01
upper_div	0.62	0.49	0.72	0.45	0.09	0.03
native	-1.05	0.22	-1.07	0.26	-0.02	0.30
tenure	-1.21	0.41	-1.23	0.42	-0.02	0.68
students	30.98	27.91	44.96	61.36	13.98	0.00
allstudents	47.27	49.84	66.85	100.48	19.58	0.01

Let's check our data... now with a Love Plot!

```
# Reads a user-written function to generate a loveplot
source("https://raw.githubusercontent.com/maibennett/sta235/main/exampleSite/content/Classes/Week3/2_PotentialOutcomes/coc

treat_id <- profs %>% mutate(id = seq(1, nrow(profs))) %>% filter(treat==1) %>% pull(-1)
control_id <- profs %>% mutate(id = seq(1, nrow(profs))) %>% filter(treat==0) %>% pull(-1)

loveplot_balance(covs, treat_id, control_id, v_line = 0.05, format = TRUE)
```

Is it enough to control?

- We can use the covariates we have on our dataset to **control for those group differences**.

	Model 1	Model 2
(Intercept)	3.998***	4.070***
	(0.025)	(0.245)
beauty	0.133***	0.141***
	(0.032)	(0.033)
minority		-0.072
		(0.077)
age		-0.003
		(0.003)
gendermale		0.221***
		(0.053)
divisionupper		-0.094*
		(0.056)
native		0.253**
		(0.110)
tenure		-0.145**
		(0.062)
allstudents		0.000
		(0.000)
Num.Obs.	463	463
F	17.085	7.193
* p < 0.1, ** p < 0.05, *** p < 0.01		

Beauty coeff. is consistent across models

Other covariates also matter

Is it enough to control?

- We can use the covariates we have on our dataset to control for those group differences.

Is that enough?

What other variable could be confounding our effect?

If I told you professors in the treatment group are taller than the ones in the control group, is height a confounder?

What about self-esteem?

Answering the question

How would you answer this question?
Design a study!

Can you "randomize" beauty?

After everything we've seen today... JITT

Is there an association between health insurance and health index?

After everything we've seen today... JITT

Is there an association between health insurance and health index?

Is there a causal effect of health insurance on health index?

After everything we've seen today... JITT

Is there an association between health insurance and health index?

Is there a causal effect of health insurance on health index?

Remember that a confounding variable needs to affect the treatment AND the outcome

Main takeaway points

Causal Inference is hard

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- Think about the causal problem

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- Think about the causal problem
- Always look at your data

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- Always look at your data
- Check validity of assumptions (*Is ignorability plausible? Am I controlling for the right covariates?*)

Main takeaway points

Causal Inference is hard

- Think about the causal problem
- Always look at your data
- Check validity of assumptions (*Is ignorability plausible? Am I controlling for the right covariates?*)
- Most of this chapter will be spent on looking for exogeneous variation to make the ignorability assumption happen.

Next week

- Randomized Controlled Trials:
  - Pros and Cons
  - Concept of validity
  - A/B Testing

References

- Angrist, J. & S. Pischke. (2015). "Mastering Metrics". *Chapter 1*.
- Cunningham, S. (2021). "Causal Inference: The Mixtape". *Chapter 4: Potential Outcomes Causal Model*.
- Neil, B. (2020). "Introduction to Causal Inference". *Fall 2020 Course*