

# STA 235 - Introduction to Causal Inference: Potential Outcomes

Spring 2021

McCombs School of Business, UT Austin

# Housekeeping

Homework 1 is due next Monday

- Check out the **R scripts** posted for each class.
- Additional slides for **interpretation of logistic regression coefficients**.

TA Office Hours: Friday 12th 4:00 - 5:00 PM

# Last week

- Finished our chapter on **multiple regression**.
- **Statistical Adjustment**: Unveiling useful associations, multicollinearity.
- **Binary Outcomes**: LPM vs Logistic Regression.



# Today



- **Introduction to Causal Inference:**

**How? Potential Outcomes Framework**

**What? Causal Estimands**

**Why? Causal Questions and Study Design**



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/10.1111/jasp.12737](https://onlinelibrary.wiley.com/doi/epdf/10.1111/jasp.12737)

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

ORIGINAL ARTICLE

Journal of Applied Social Psychology WILEY

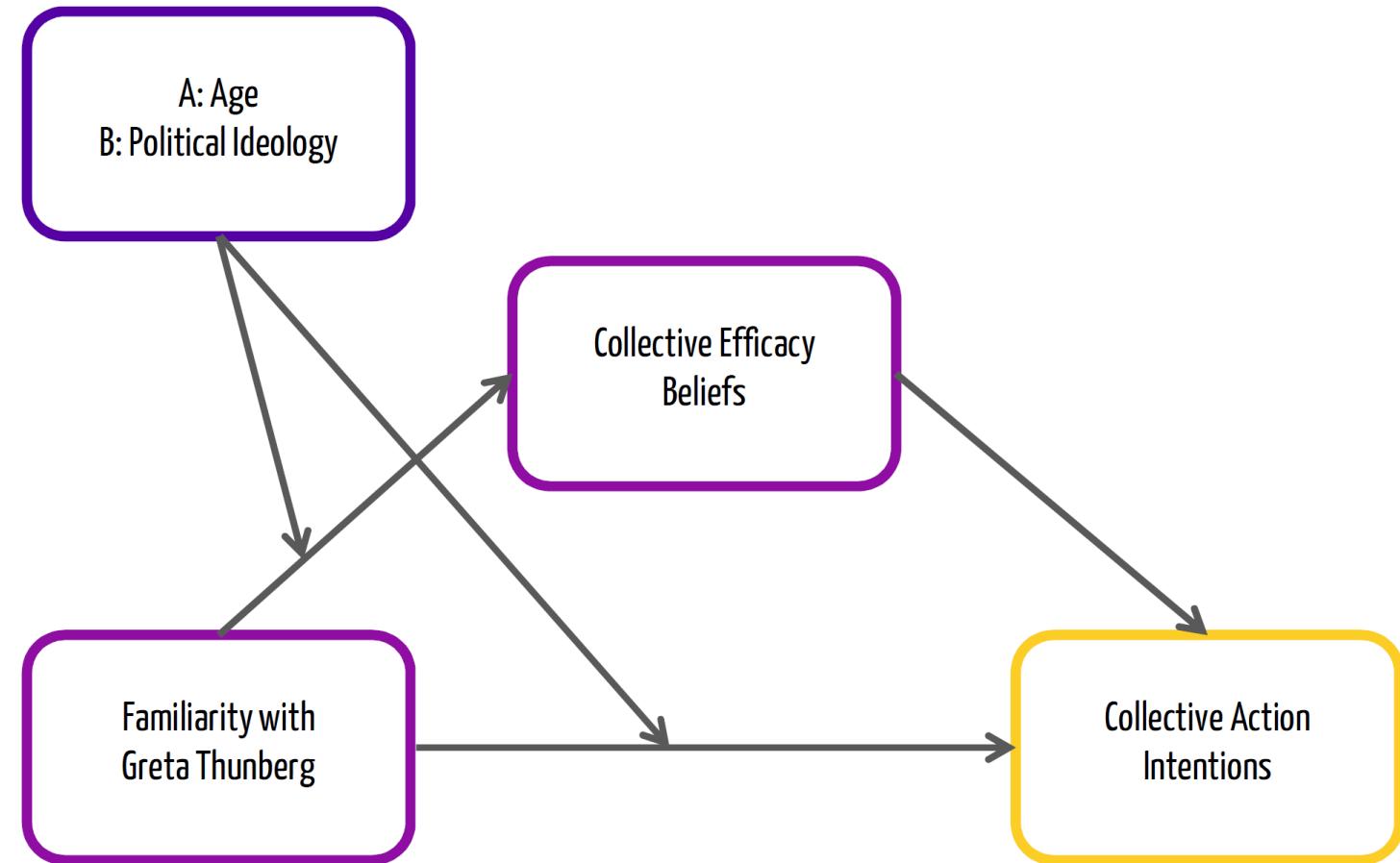
**The Greta Thunberg Effect: Familiarity with Greta Thunberg predicts intentions to engage in climate activism in the United States**

Anandita Sabherwal<sup>1</sup> | Matthew T. Ballew<sup>2</sup> | Sander van der Linden<sup>1</sup> |  
Abel Gustafson<sup>3</sup> | Matthew H. Goldberg<sup>4</sup> | Edward W. Maibach<sup>5</sup> |  
John E. Kotcher<sup>6</sup> | Janet K. Swim<sup>6</sup> | Seth A. Rosenthal<sup>6</sup> | Anthony Leiserowitz<sup>6</sup>

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<sup>2</sup>Cran College of Health and Behavioral Sciences, Chapman University, Orange, CA, USA  
<sup>3</sup>Department of Communication, University of Cincinnati, Cincinnati, OH, USA  
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<sup>5</sup>Mason Center for Climate Change Communication, George Mason University, VA, USA

**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



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...](https://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 [f Facebook](#) [Twitter](#) [Pinterest](#) [in 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](#)

# 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".

# What is Causal Inference?

**Inferring the effect of one thing on another thing**

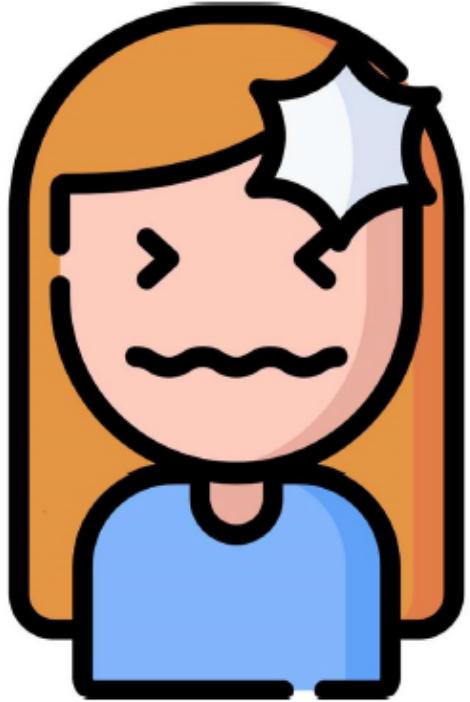
- "My headache went away because I took an aspirin".
- "The new marketing campaign increased our sales by 20%"

# What is Causal Inference?

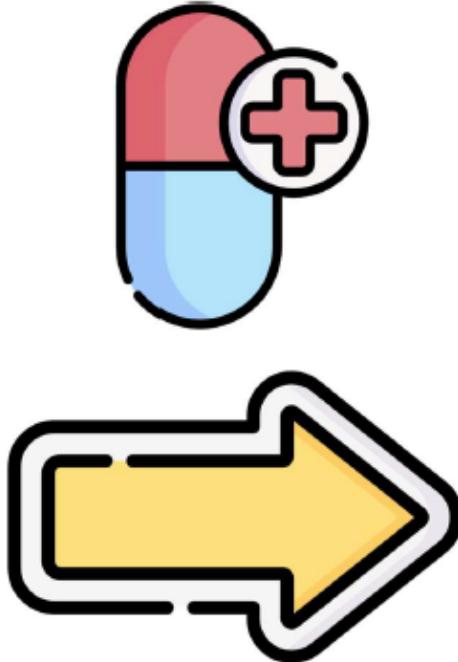
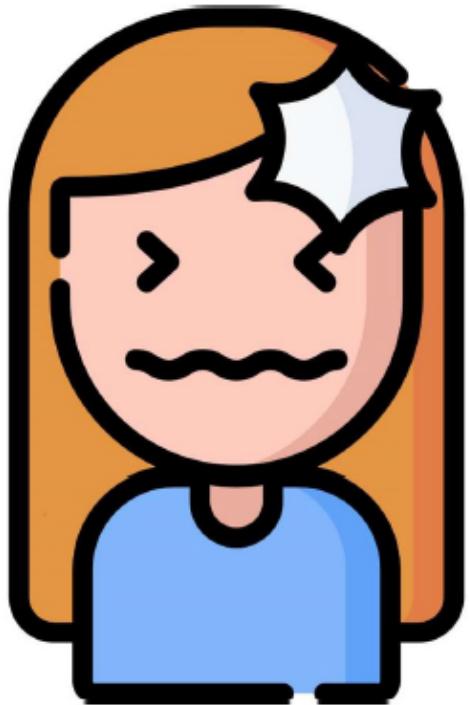
**Inferring the effect of one thing on another thing**

- "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."

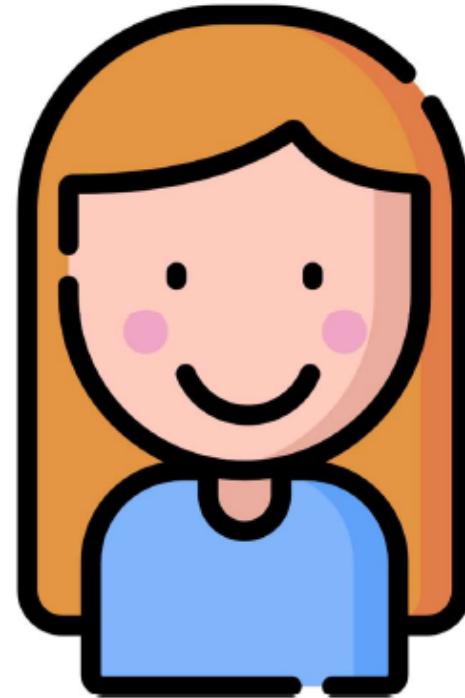
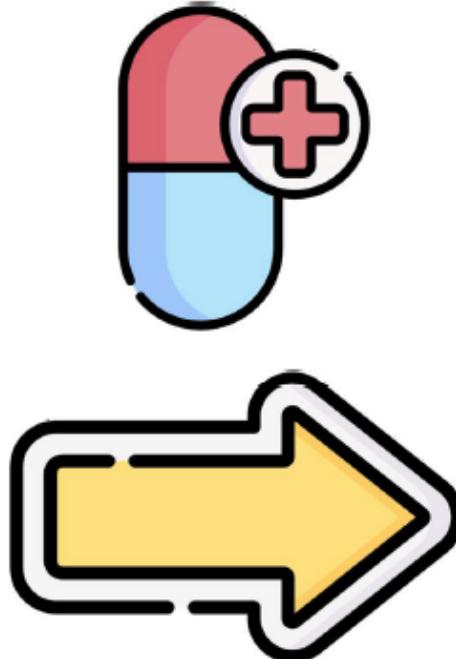
# Imagine we have a headache...



# 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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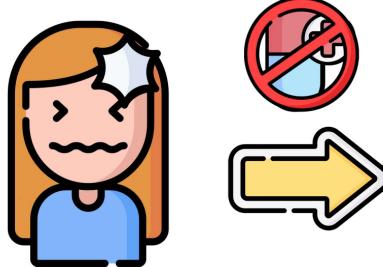
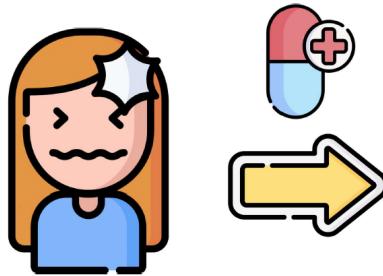
# A world of potential (outcomes)

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

$$Y_i|Z_i = 1 \stackrel{\Delta}{=} Y_i(1)$$

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

In the same fashion,

$$Y_i|Z_i = 0 \stackrel{\Delta}{=} Y_i(0)$$

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

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

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Can we ever observe individual causal effects?

# Causal Effects

## Individual Causal Effect

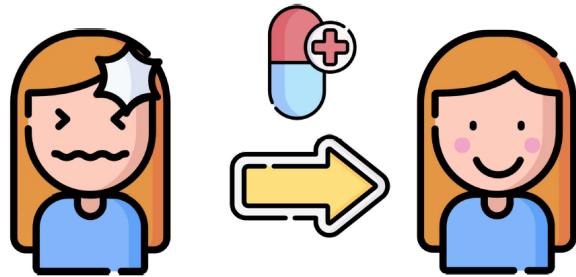
$$ICE_i = Y_i(1) - Y_i(0)$$

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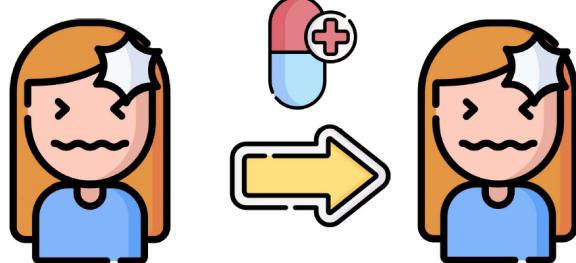
No!\*

# Only one realization

$Z=1$

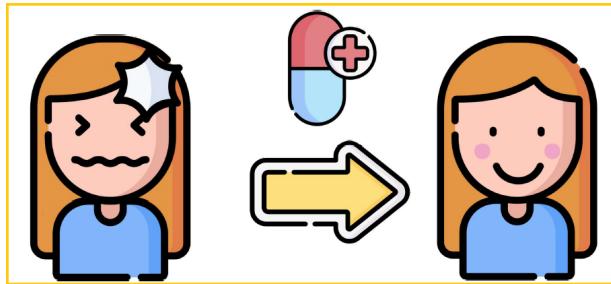


$Z=0$

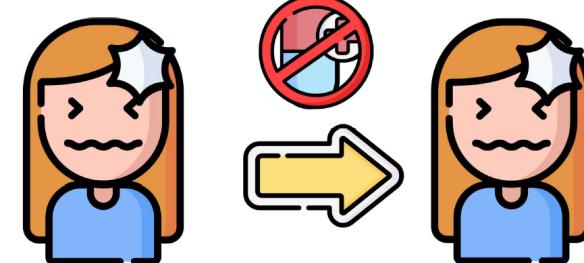
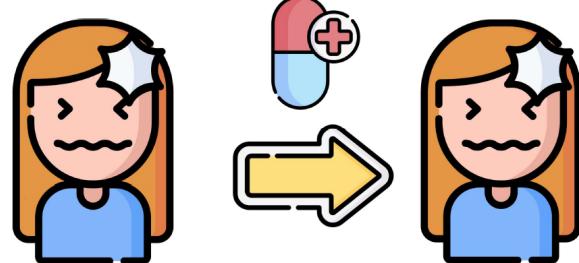
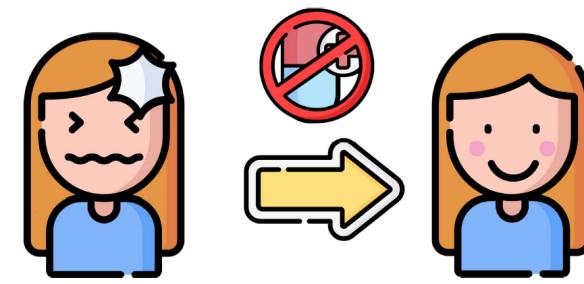


# Only one realization

$Z=1$



$Z=0$



# 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

$$\mu$$

## 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	?
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# Getting around the fundamental problem of causal inference

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

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

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- What is the **estimator**?

Difference in sample means

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Difference in sample means

- 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

# Under what assumptions is our estimate causal?

We are using:

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

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?

$$\begin{aligned}\tau &= E[Y_i(1) - Y_i(0)] \\ &= E[Y_i(1)] - E[Y_i(0)]\end{aligned}$$

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

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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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# 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	
2	1	1	1		
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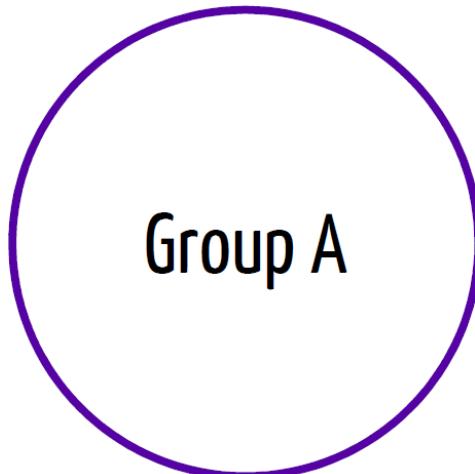
We can just "ignore" the missing data problem:

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		
			1/3	2/3	

# Ignorability Assumption

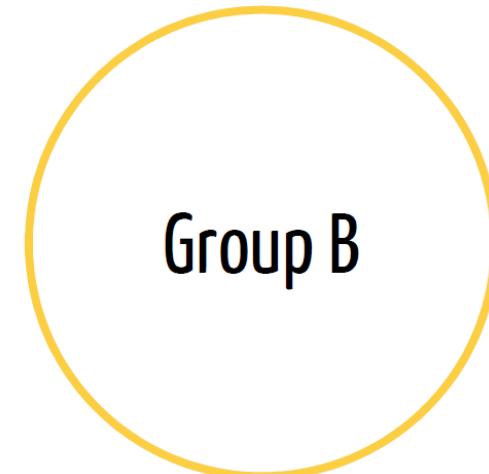
It's the same as the **exchangeability assumption**:

$$Z = 1$$



$$E[Y|Z = 1] = y_1$$

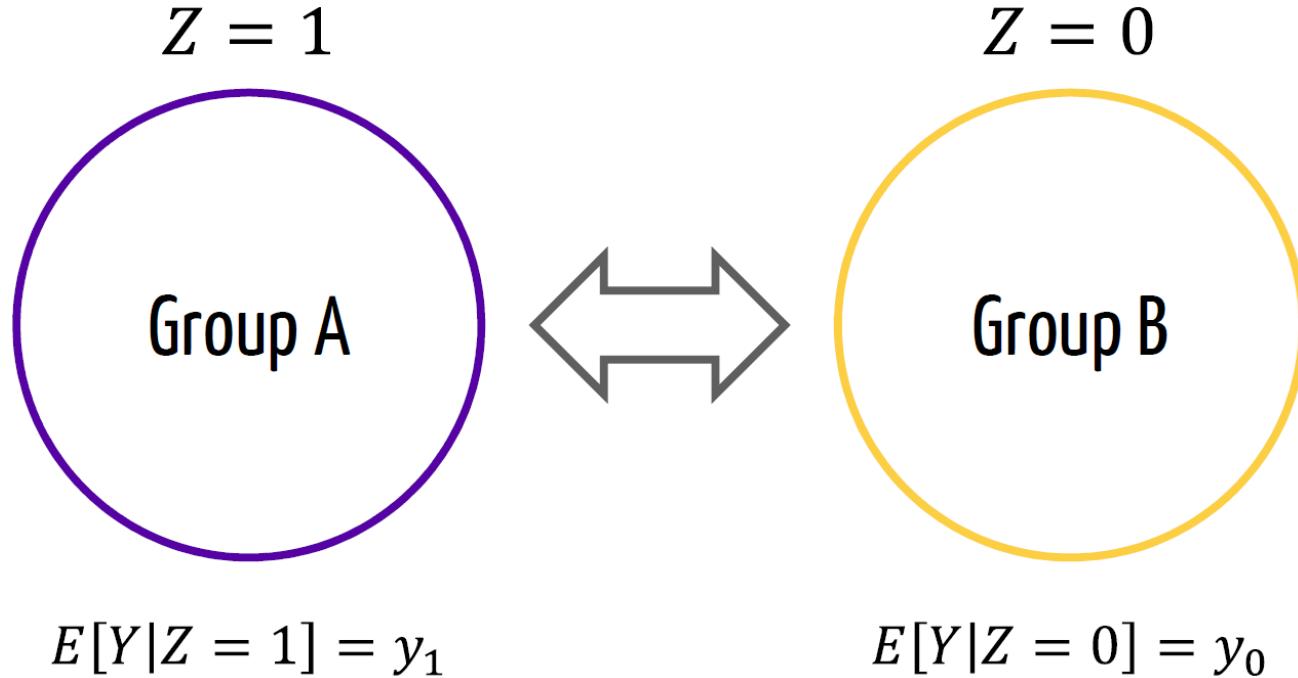
$$Z = 0$$



$$E[Y|Z = 0] = y_0$$

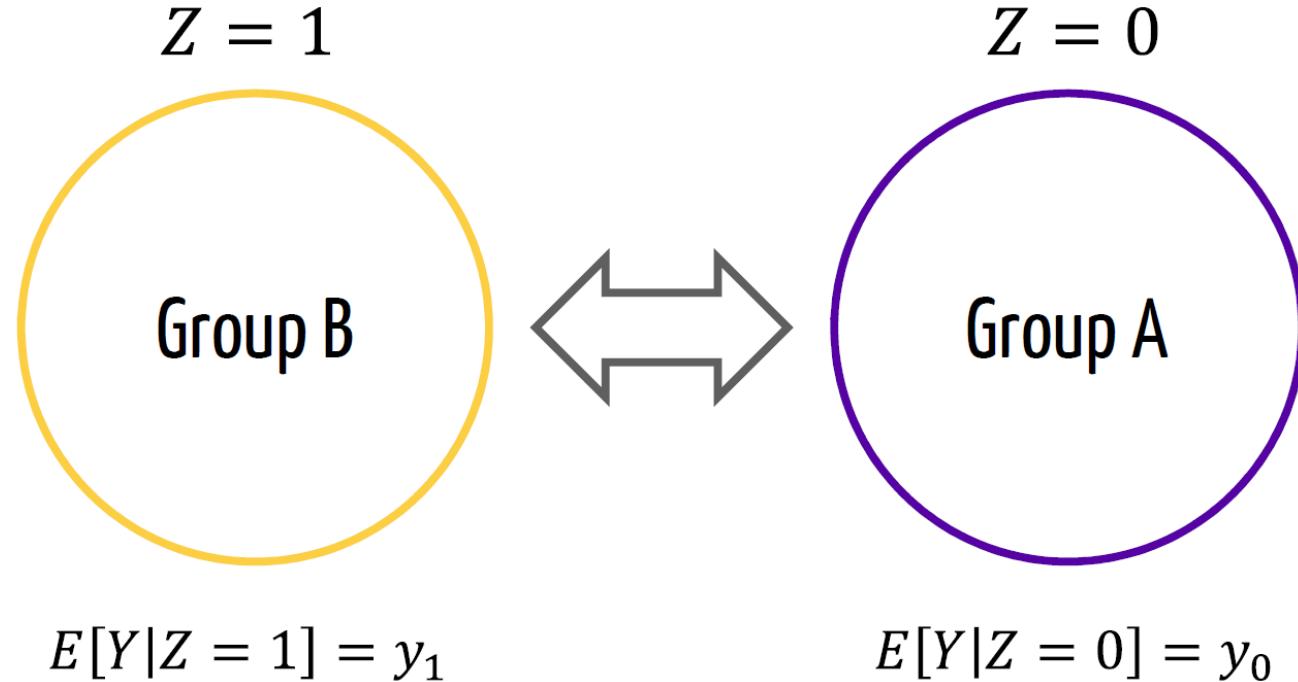
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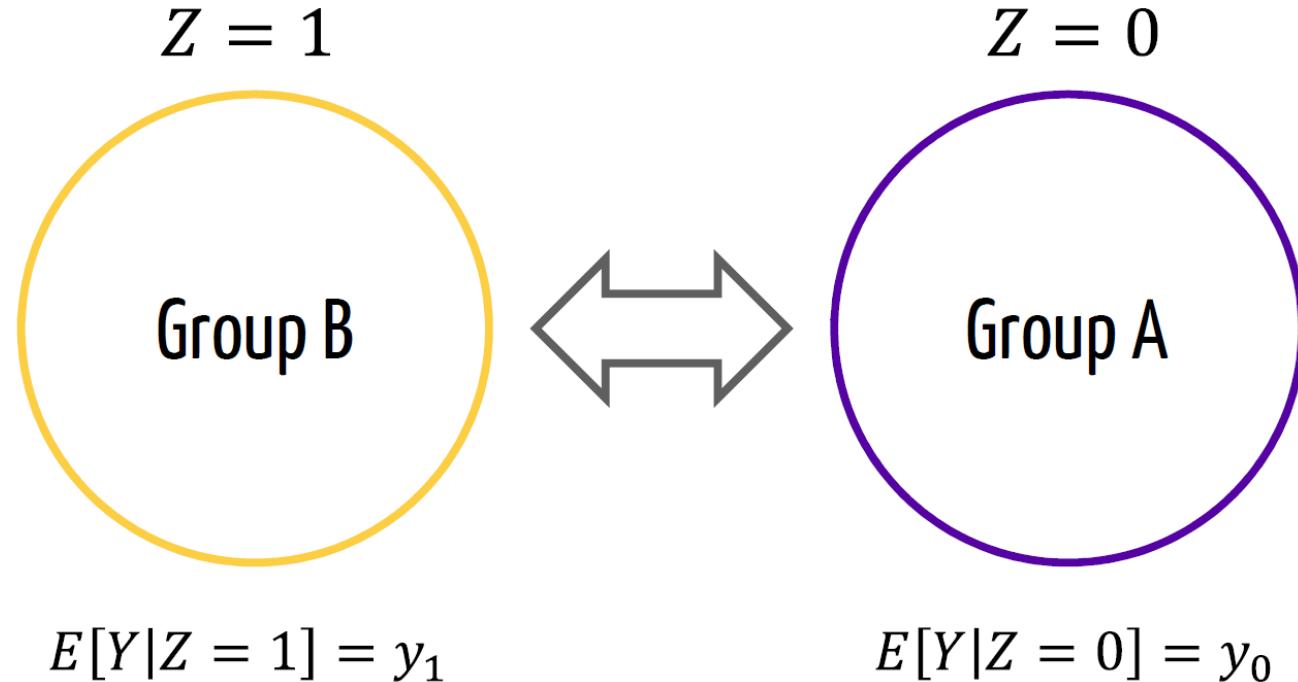
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# Ignorability Assumption

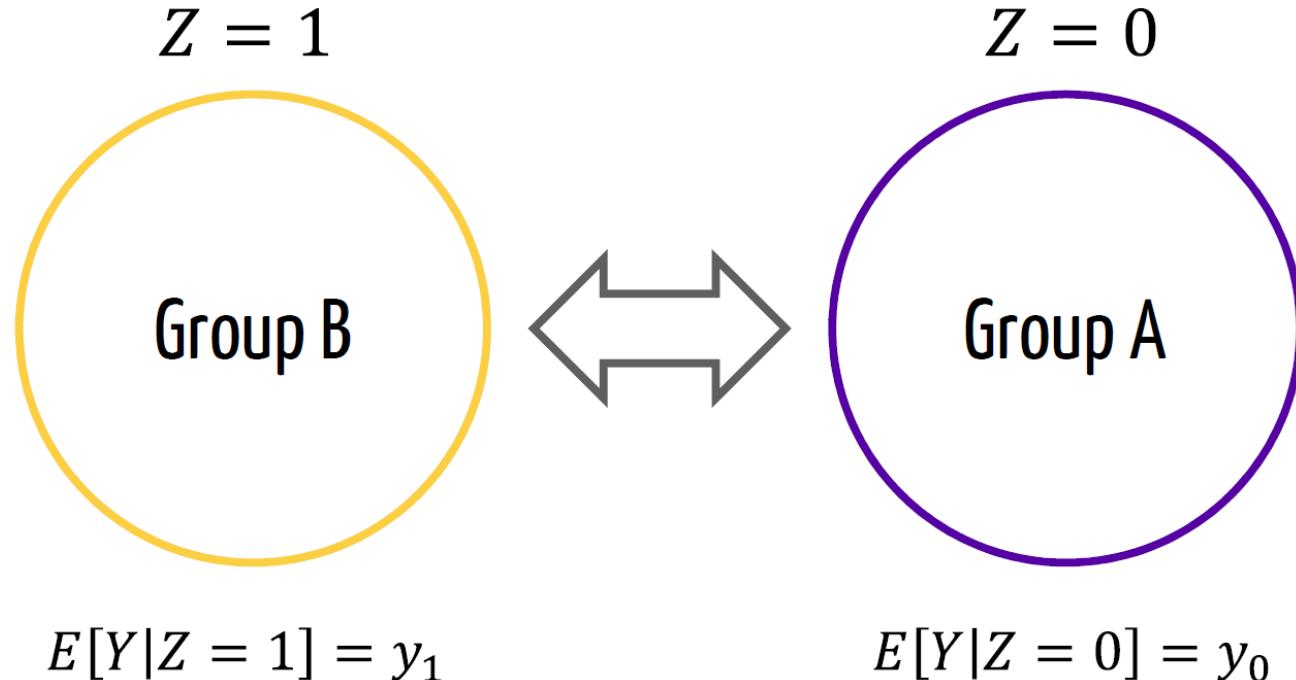
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$$E[Y(1)|T = 1] = E[Y(1)|Z = 0] = E[Y(1)]$$

# Ignorability Assumption

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



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

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

# 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  $(Y(0), Y(1)) \not\perp\!\!\!\perp Z$

$$\begin{aligned}\tau &= E[Y_i(1) - Y_i(0)] = \\ &= E[Y_i(1) - Y_i(0)|Z = 1]Pr(Z = 1) + E[Y_i(1) - Y_i(0)|Z = 1](1 - Pr(Z = 1))\end{aligned}$$

# 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:

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

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

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

$$- (1 - Pr(Z=1))(ATT - ATC)$$

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:

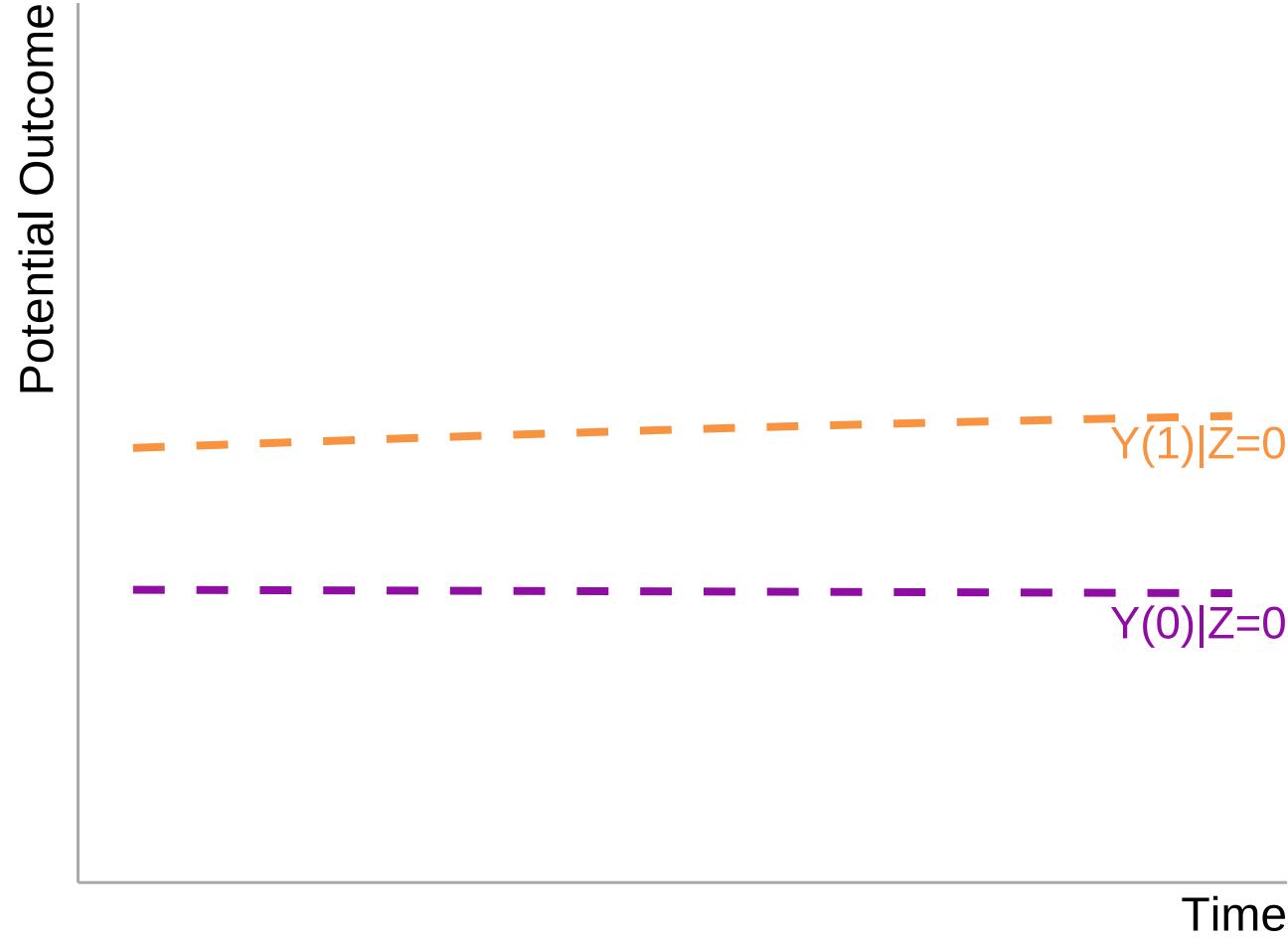
$$\tau = E[Y_i(1) - Y_i(0)] = ATE$$

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

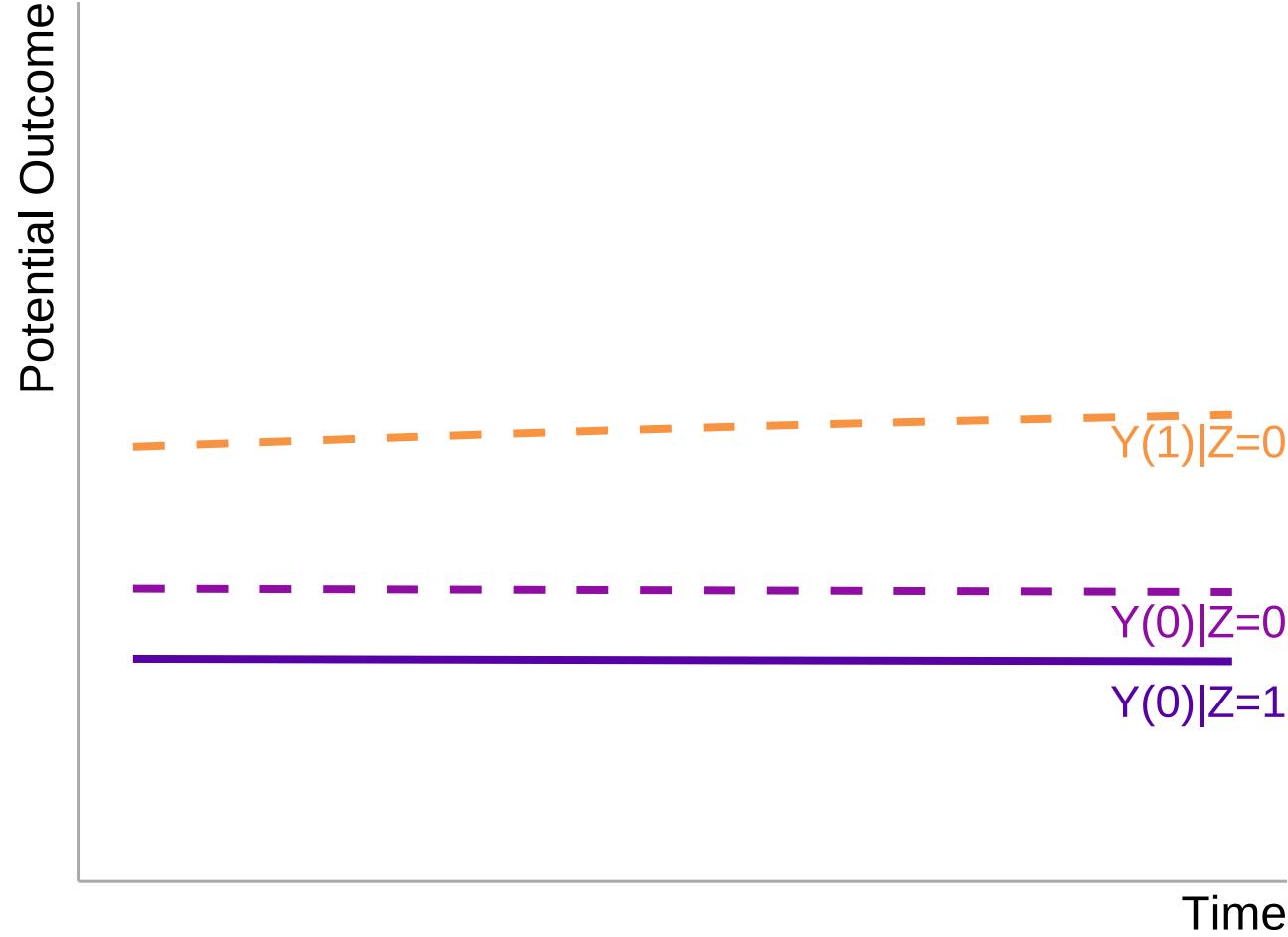
- Selection Bias:** Difference between groups if they both were under control.
- Heterogeneous Treatment Effect Bias:** Difference in returns to treatment for the two groups (weighted by the control population).

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

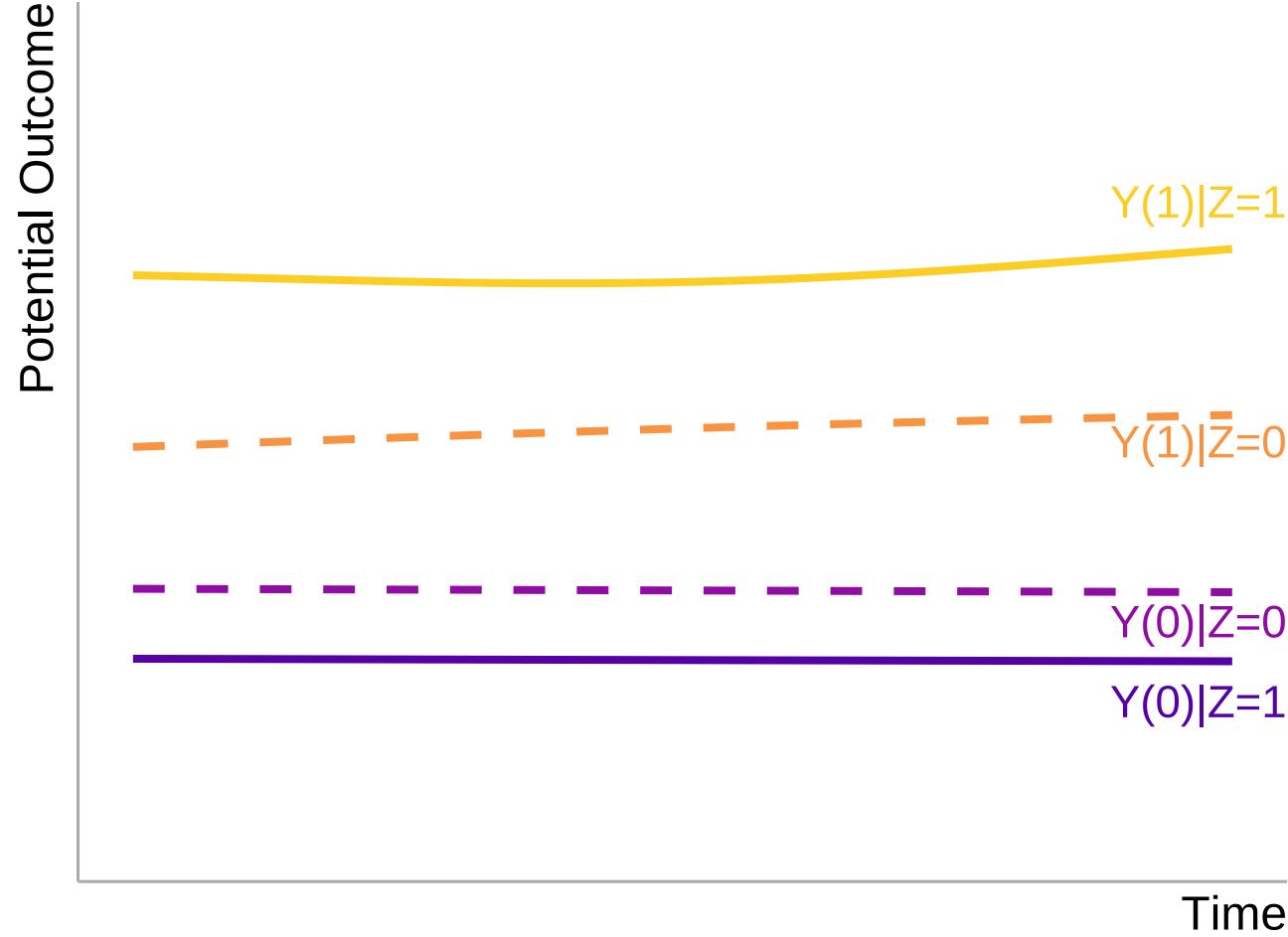
# How would bias look like?



# How would bias look like?



# How would bias look like?



Let's look at some data

# Example: Effect of types of advertising on sales

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



**freshdirect**  
The freshest groceries. Delivered.

Hey Bellport, get everything you need to grill, thrill, and chill, delivered all summer long!

**\$25 OFF\***  
YOUR NEXT ORDER OF \$99+  
**USE CODE: BEACH10**

A photograph of various grocery items from FreshDirect, including a bottle of olive oil, a carton of organic milk, a box of eggs, a bag of flour, a watermelon, a head of lettuce, several tomatoes, a lemon, a peach, and a bag of oranges.

Fresh-picked produce | Farm-fresh dairy | Custom-cut meats  
Sustainable seafood | Your favorite grocery brands | Hundreds of weekly deals  
Plus FreshDirect Wines & Spirits

\*This offer for \$25 Off is good on your next residential order delivered when promo code BEACH10 is entered at checkout. May not be combined with any other promotion code. Valid only for your order totaling \$99 or more before taxes, delivery fee, and delivery premium. Limit: one per customer/household. All standard customer terms and conditions apply. FreshDirect reserves the right to cancel or modify the offer at any time. Offer expires at 11:59pm ET, September 1, 2019 and will be removed from orders that are modified after this time. Offer is nontransferrable. Void where prohibited. Offer is limited time only. ©2019 Fresh Direct, LLC.

# Example: Effect of types of advertising on sales

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

- What is the **treatment**?

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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 it 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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(290/1500)

(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

- 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)

**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?

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Depends

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- **Measured before the intervention:** Yes → Getting your name out there is effective, especially for people that don't know you.
- **Measured after the intervention:** Don't know → Intervention might have incentivized people to go to the website, and registering also had an effect on traffic.

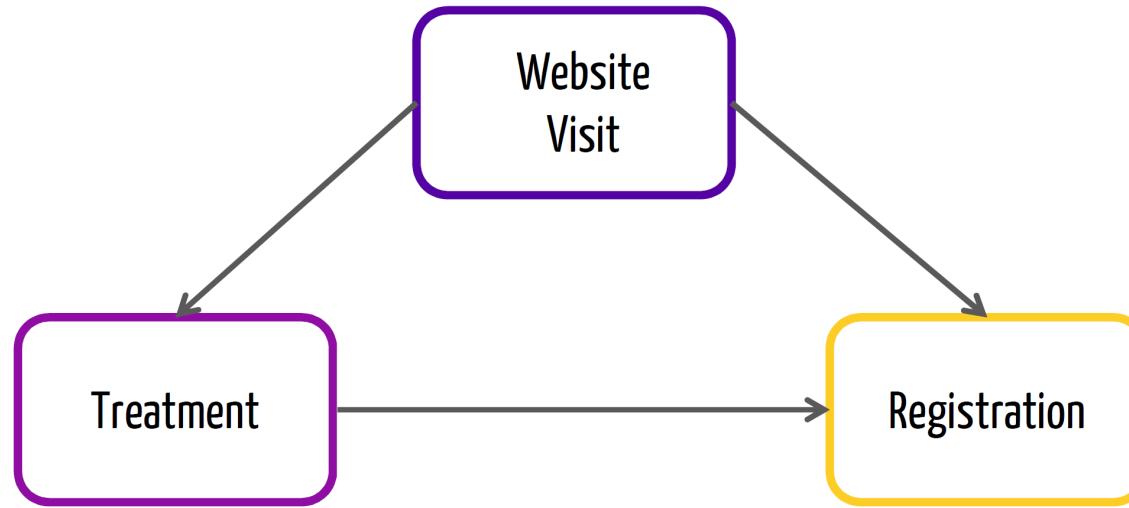
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Depends

- **Measured before the intervention:** Yes → Getting your name out there is effective, especially for people that don't know you
- **Measured after the intervention:** Don't know → Intervention might have incentivized people to go to the website, and registering also had an effect on traffic.

Collider

# Scenario 1: Confounding



# Scenario 1: Confounding

## Data Generating Process:

- No treatment effect.
- $\Pr(\text{Registering} \mid \text{Visit}) < \Pr(\text{Registering} \mid \text{Not Visited})$
- 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**?

```
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))
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```
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

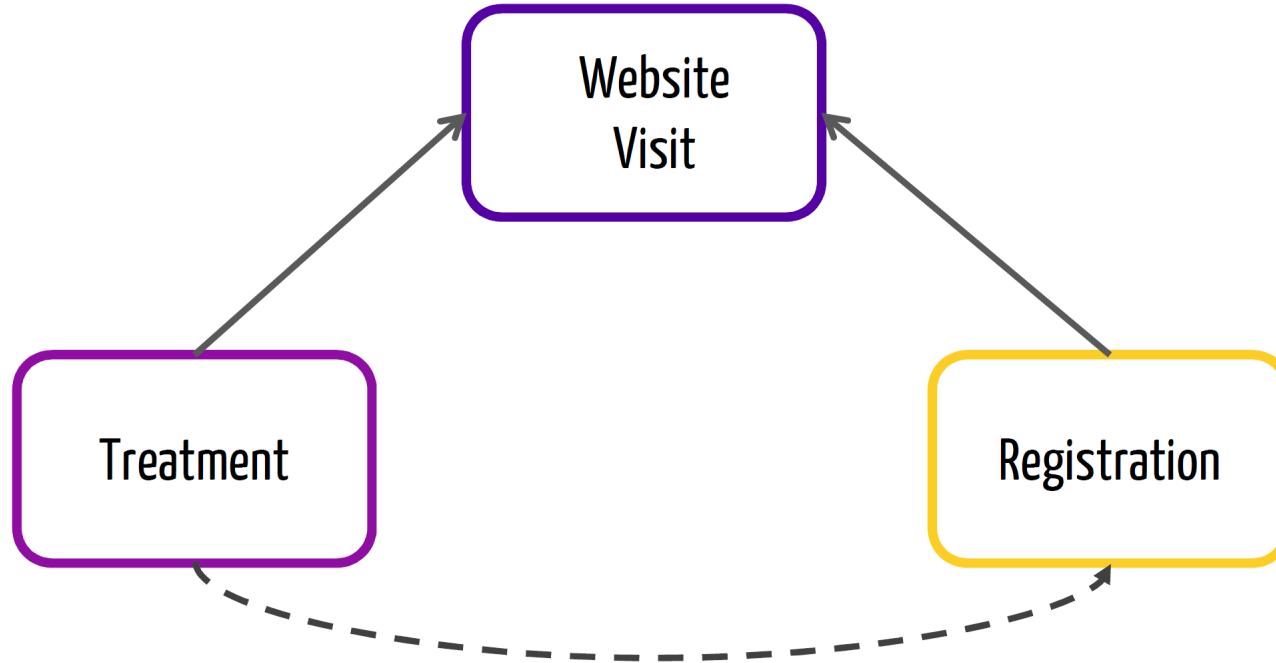
What happens if we now **control by whether the person visited the website?**

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

##
## Call:
## lm(formula = y ~ factor(treat) + visit, data = confound)
##
## Residuals:
##     Min      1Q      Median      3Q      Max 
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```

- **What conclusions would you make?**

## Scenario 2: Collider Bias



# Scenario 2: Collider Bias

## Data Generating Process:

- No direct treatment effect of mailing over emails.
- $\text{Pr}(\text{Visit} \mid \text{e-mail}) < \text{Pr}(\text{Visit} \mid \text{mail})$
- 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**?

```
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) -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?**

```
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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
```

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

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

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## (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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# 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

```
profs <- read.csv("https://raw.githubusercontent.com/maibennett/sta235/main/exampleSite/content/Classes/Week3/1_
                     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?

```
library(estimatr)
summary(estimatr::lm_robust(eval ~ beauty, data=profs))

##
## Call:
## estimatr::lm_robust(formula = eval ~ beauty, data = profs)
##
## Standard error type: HC2
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF
## (Intercept) 3.998     0.02535 157.725 0.000e+00 3.94846  4.0481 461
## beauty      0.133     0.03238   4.108 4.728e-05  0.06937  0.1966 461
##
## Multiple R-squared:  0.03574 ,   Adjusted R-squared:  0.03364
## F-statistic: 16.87 on 1 and 461 DF,  p-value: 4.728e-05
```

Clearly not causal

# Beauty and Evaluations

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

Negative correlation between **residuals** and **number of students**

# 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(designmatch)

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

meantab(covs, profs$treat, which(profs$treat==1), which(profs$treat==0))
```

# Let's check our data

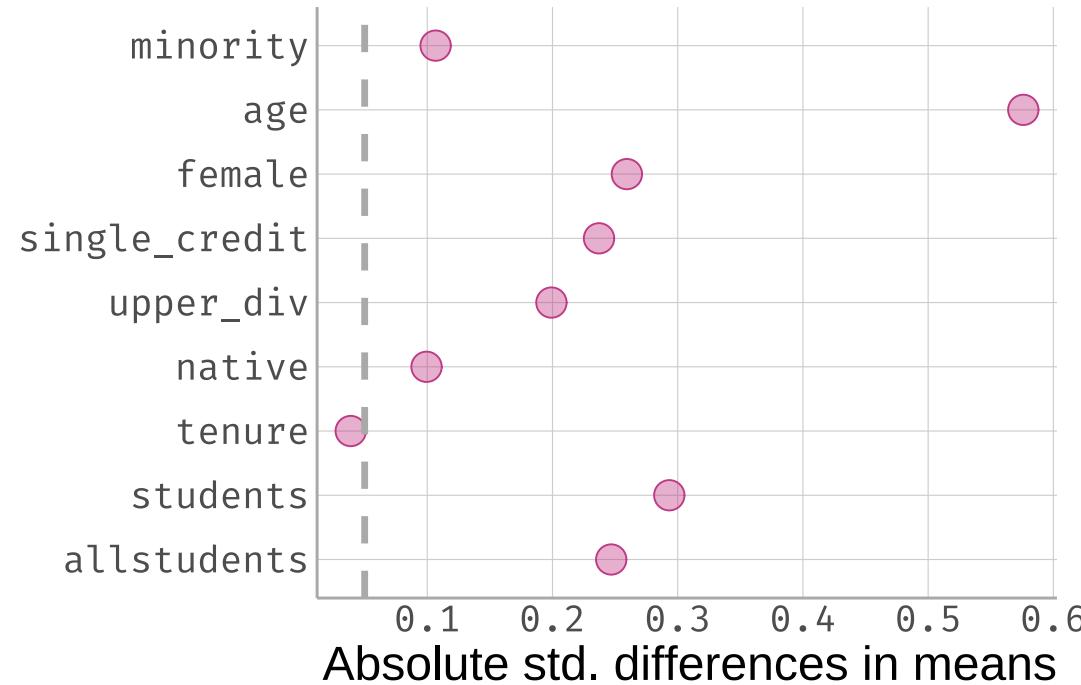
```
meantab(covs, profs$treat, which(profs$treat==1), which(profs$treat==0))
```

```
##           Mis Min Max Mean T Mean C Std Dif P-val
## minority      0   0   1   0.16  0.12   0.11  0.27
## age            0  29  73  45.12 50.56  -0.58  0.00
## female         0   0   1   0.50   0.37   0.26  0.01
## single_credit  0   0   1   0.03   0.08  -0.24  0.01
## upper_div      0   0   1   0.72   0.62   0.20  0.03
## native          0   0   1   0.93   0.95  -0.10  0.30
## tenure          0   0   1   0.77   0.79  -0.04  0.68
## students        0   5 380  44.96 30.98   0.29  0.00
## allstudents     0   8 581  66.85 47.27   0.25  0.01
```

- **What can you say about the data?**

# 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/Week3/1_Potentialou
loveplot_balance(covs, which(profs$treat==1), which(profs$treat==0), 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**.

	<b>Model 1</b>	<b>Model 2</b>
(Intercept)	3.998*** (0.025)	3.955*** (0.178)
beauty	0.133*** (0.032)	0.127*** (0.030)
minority		-0.077 (0.075)
age		-0.003 (0.003)
gendermale		0.229*** (0.053)
divisionupper		-0.123** (0.054)
native		0.250** (0.104)
tenure		-0.134** (0.059)
students		0.008*** (0.002)
allstudents		-0.005*** (0.001)
Num.Obs.	463	463
se_type	HC2	HC2
* 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?

# Is it enough to control?

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Is that enough?

What other variable could be confounding our effect?

# Is it enough to control?

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

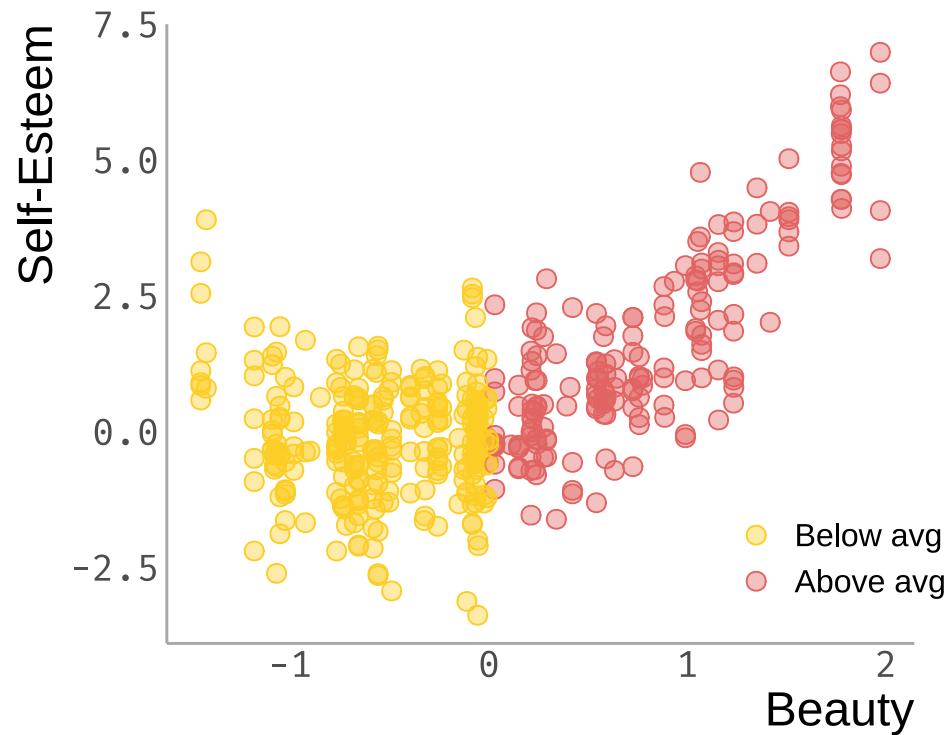
Is that enough?

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?

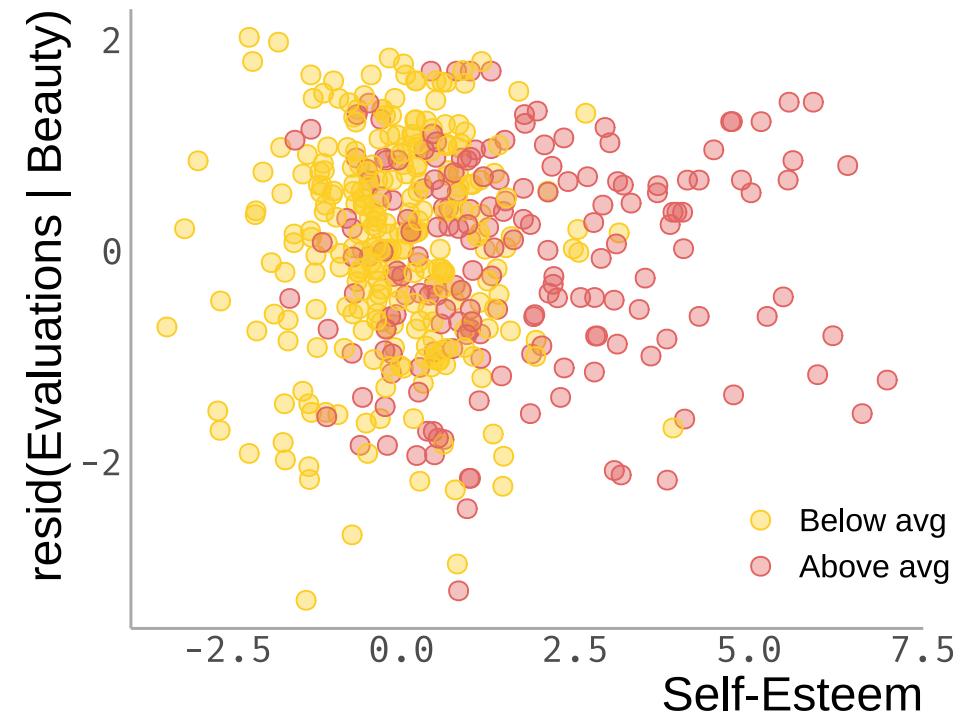
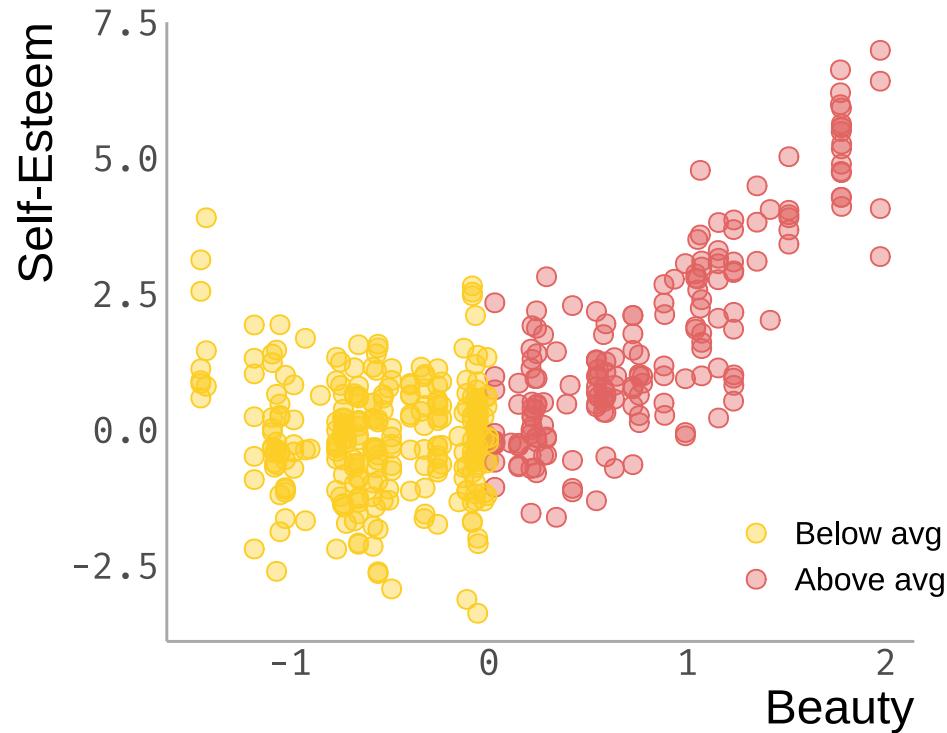
# The problem with self-esteem

- Imagine now we also have a self-esteem measure for each professor:



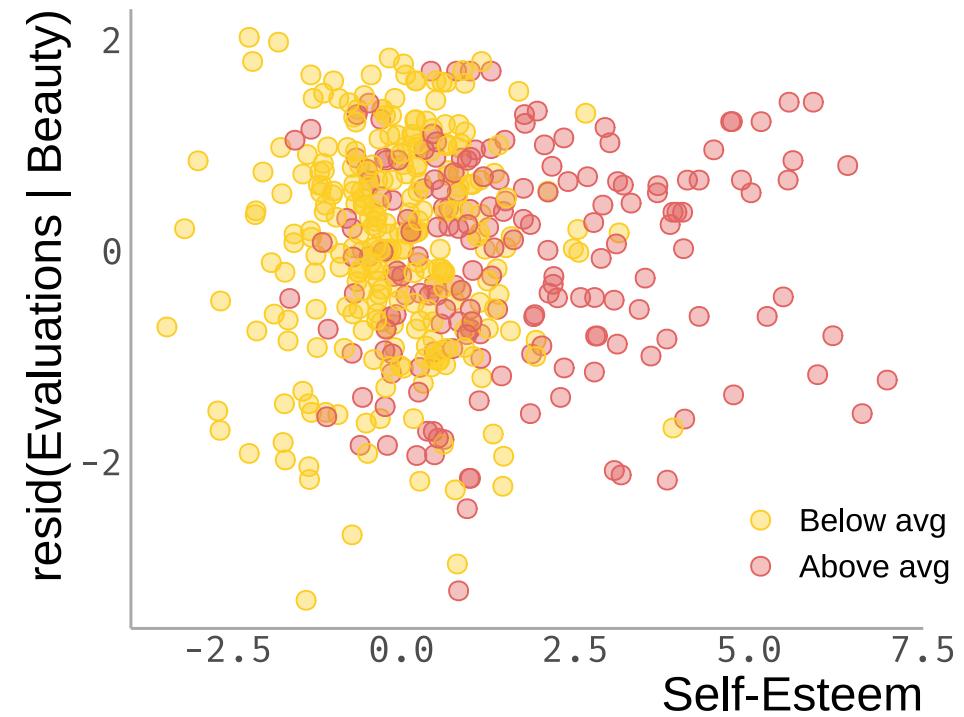
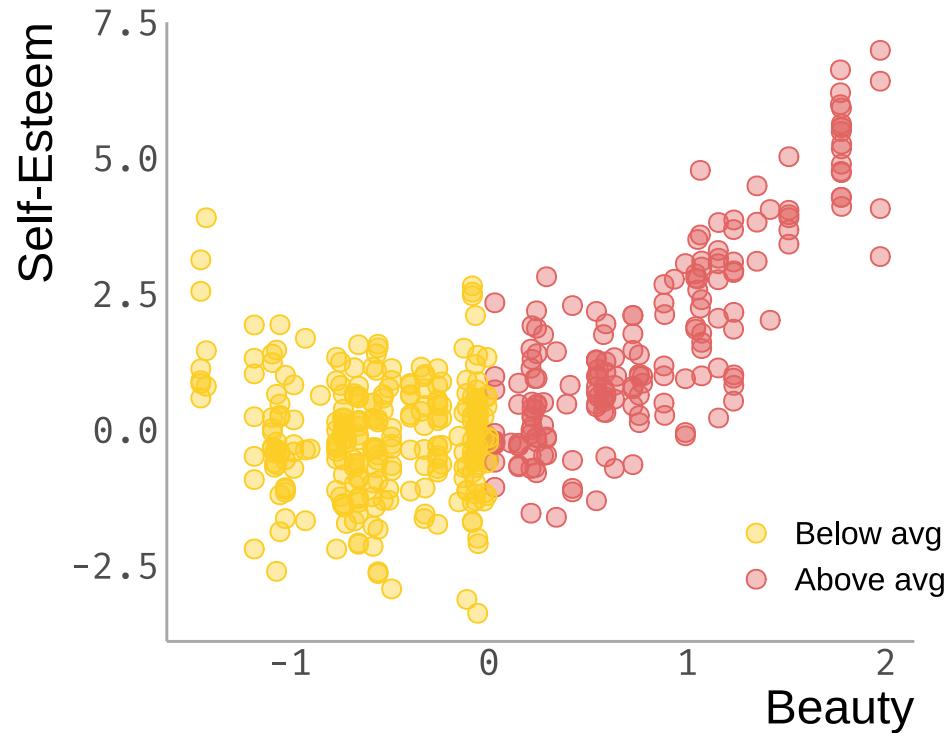
# The problem with self-esteem

- Imagine now we also have a self-esteem measure for each professor:



# The problem with self-esteem

- Imagine now we also have a self-esteem measure for each professor:



Is it potentially a **confounder**?

# Answering the question

How would you answer this question?  
Design a study!

# 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... JTT

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... JTT

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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- 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

- **Randomization inference**
- **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*