

# STA 235H - Randomized Controlled Trials II

Fall 2022

McCombs School of Business, UT Austin

# Some announcements

- Homework 3 is due this Friday.
- Answer Key for Homework 2 will be posted on Wednesday.
- Remember Idea + Data Pitch is due next week: Don't leave it to the last minute.
  - Idea needs to be approved.

Catch-up Session this Friday

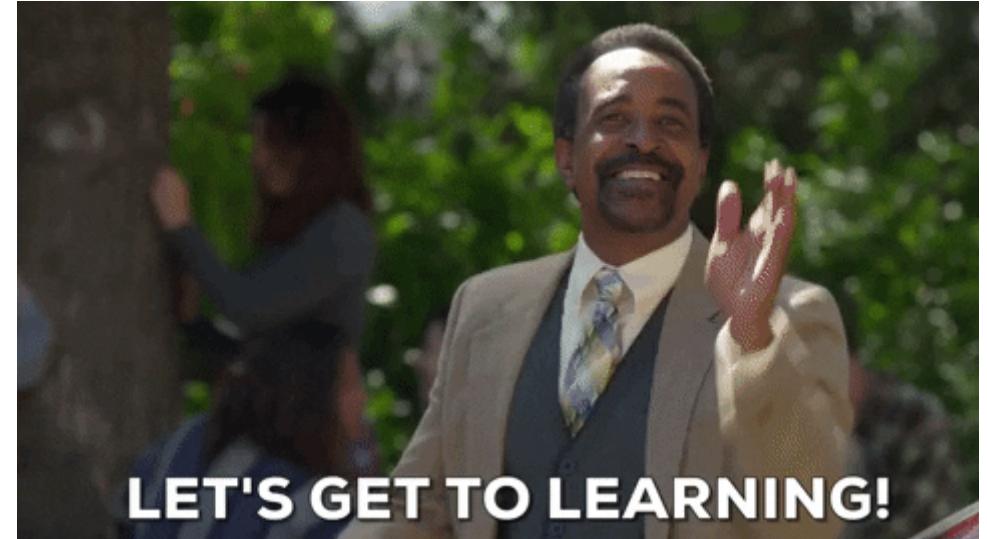
# Last week



- Continued discussing the **potential outcomes framework**.
- Introduced the **ignorability assumption**:
  - Potential outcomes  $Y(0)$  and  $Y(1)$  are independent of the treatment  $Z$
- Introduced **Randomized Controlled Trial**

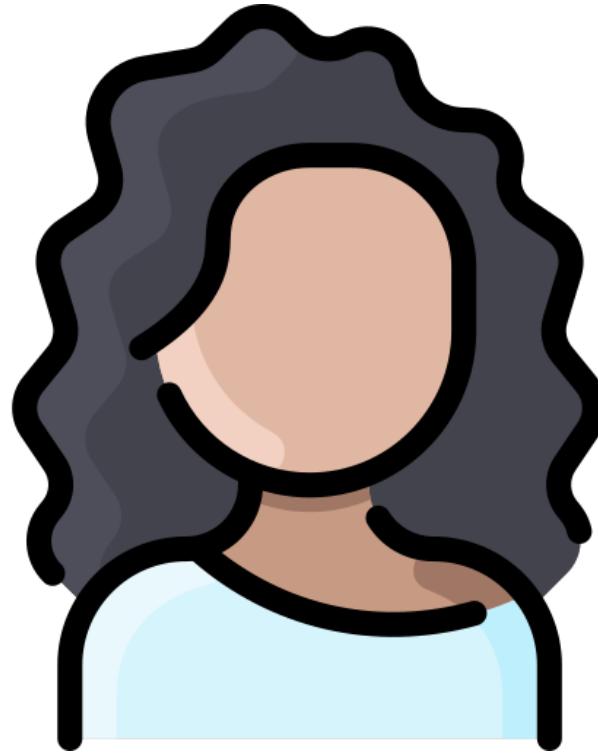
# Today

- Continue with **Randomized Controlled Trials**:
  - Design
  - Limitations
- What about **selection on observables?**:
  - Types of bias
  - Matching



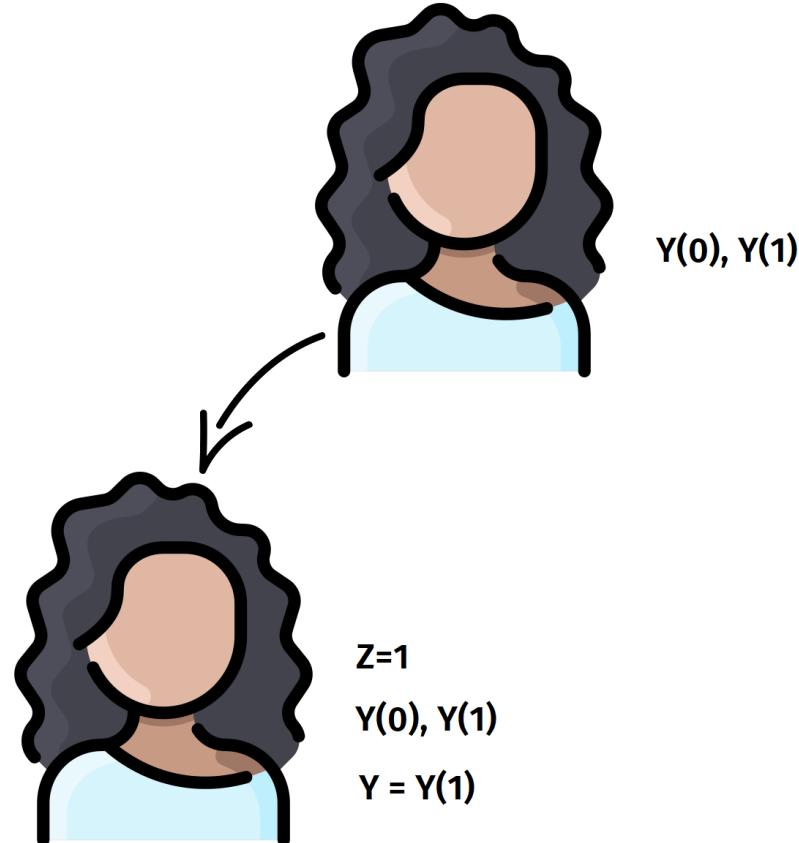
## Reviewing the Ignorability Assumption

Imagine we have an individual...

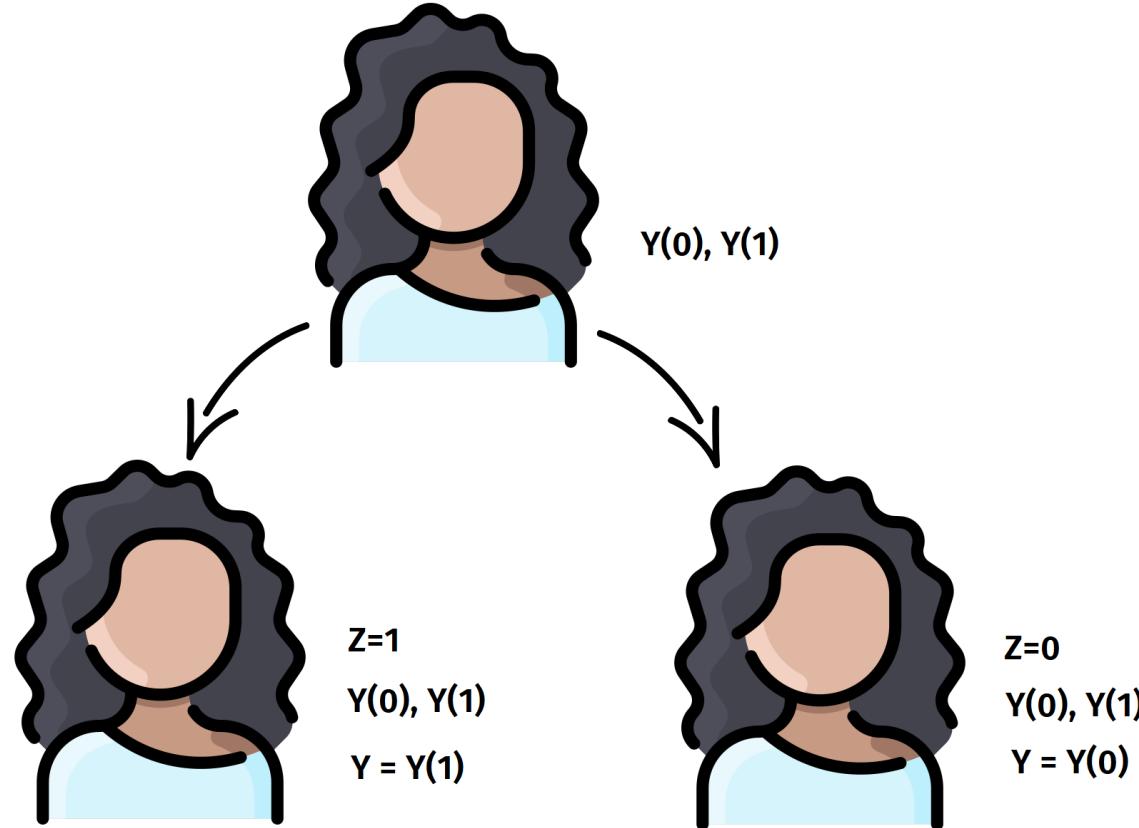


$\gamma(0), \gamma(1)$

That person could choose to take the treatment...



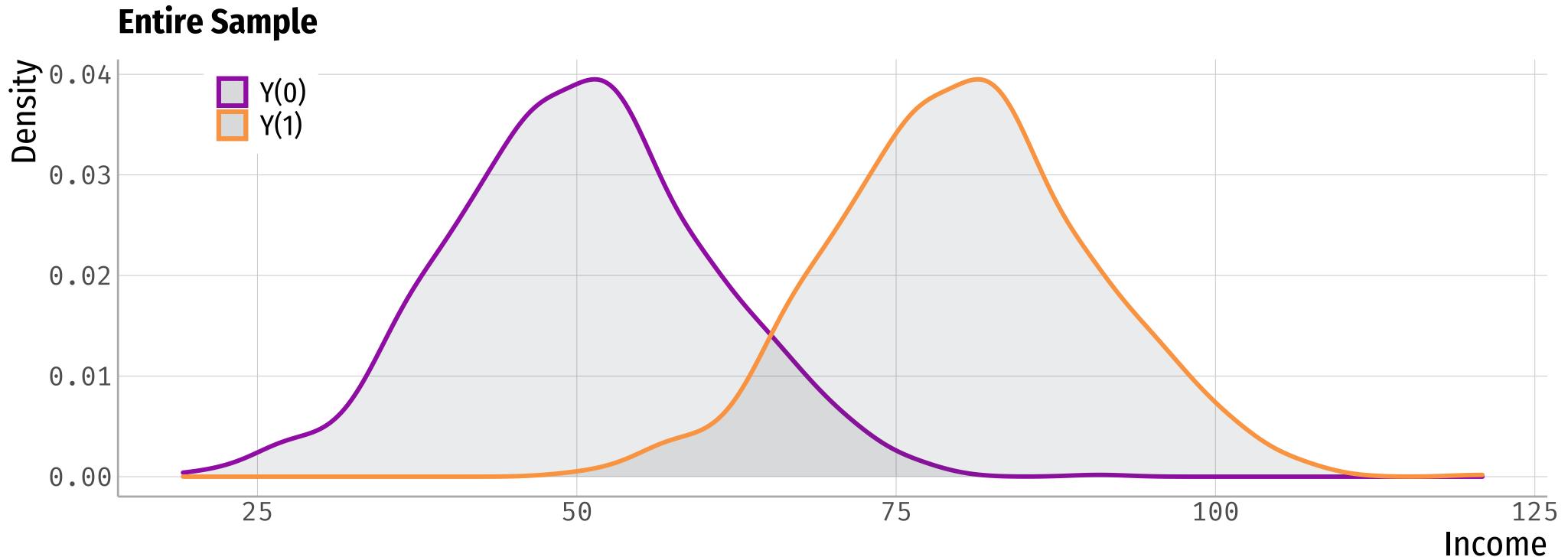
# ... or not take the treatment



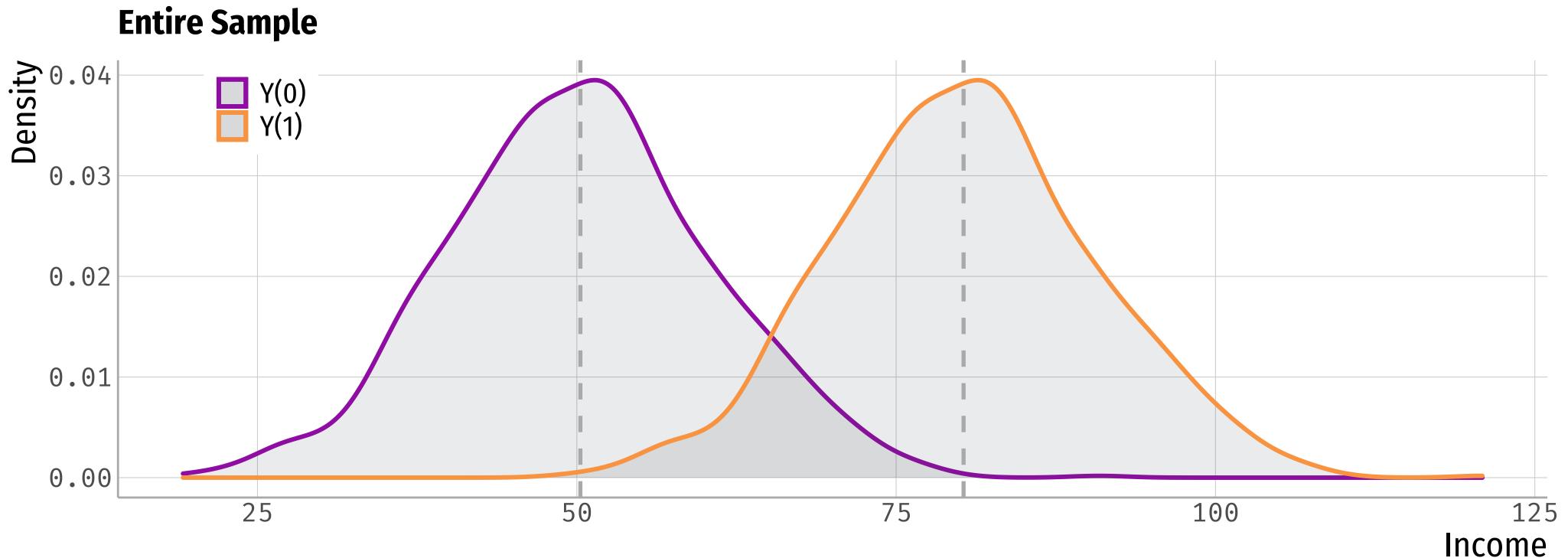
- Note that in each scenario, she still has **both potential outcomes!**

**What is the effect of going to college on future income?**

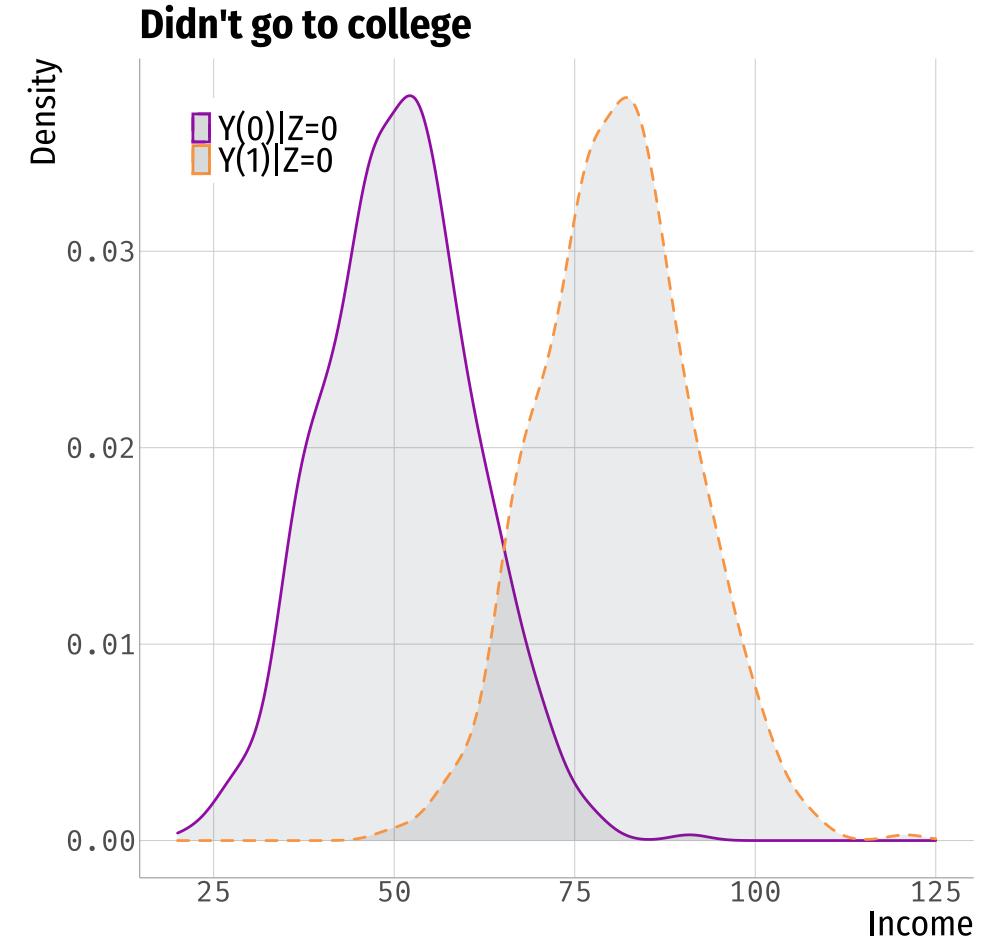
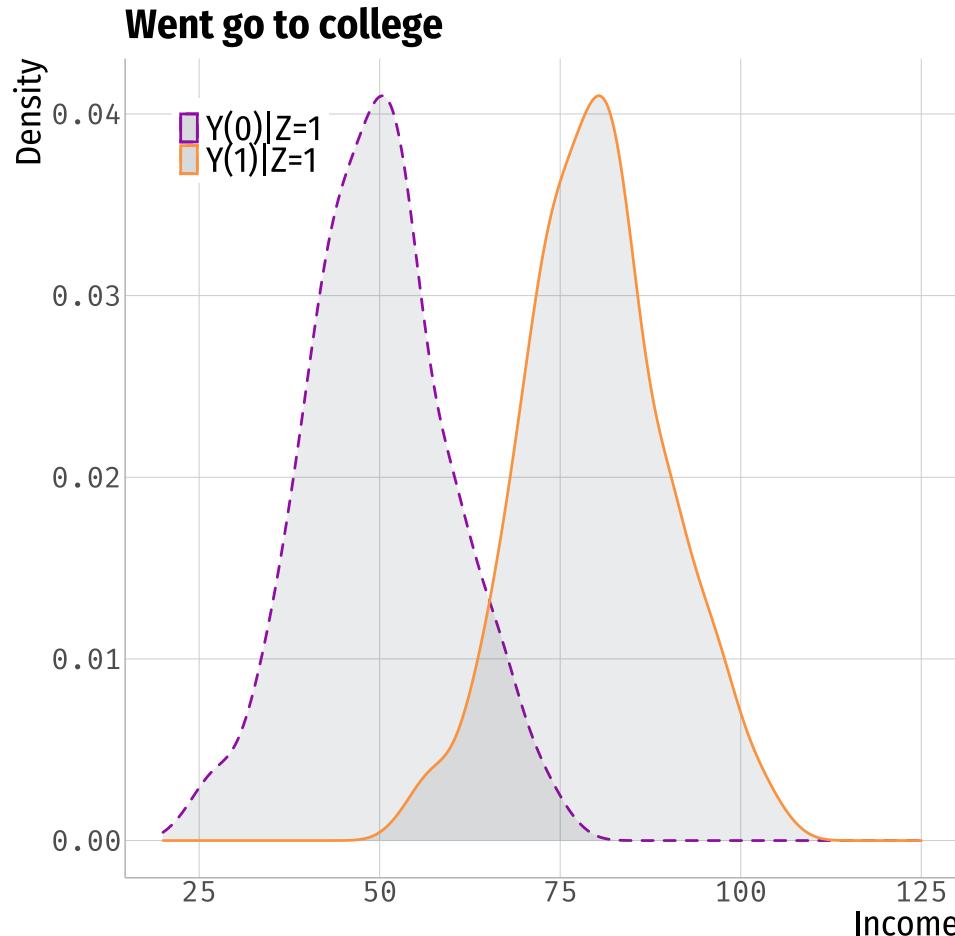
# Let's see the distributions of people



# Let's see the distributions of people



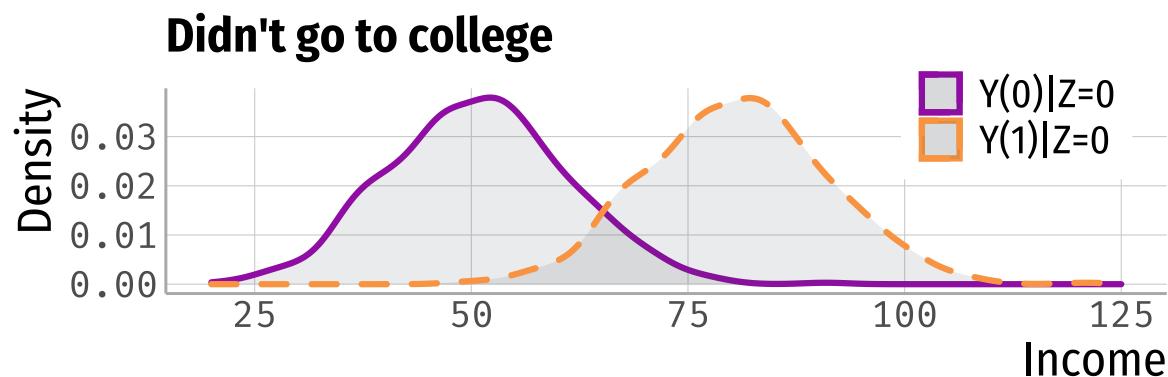
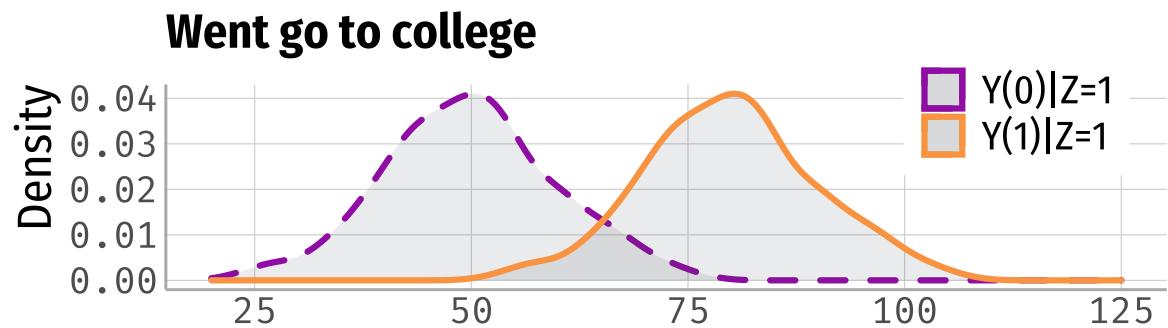
# We can only observe one distribution per group!



# Under Ignorability Assumption

$Y(0), Y(1) \perp\!\!\!\perp Z$

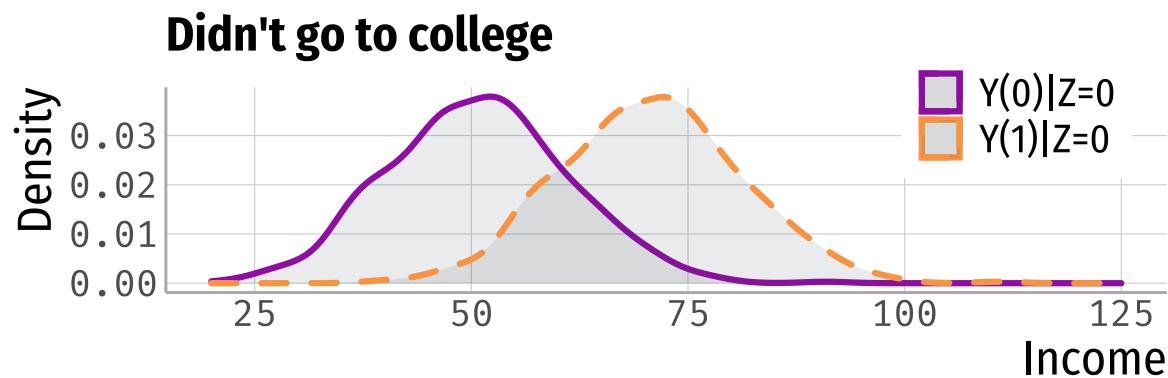
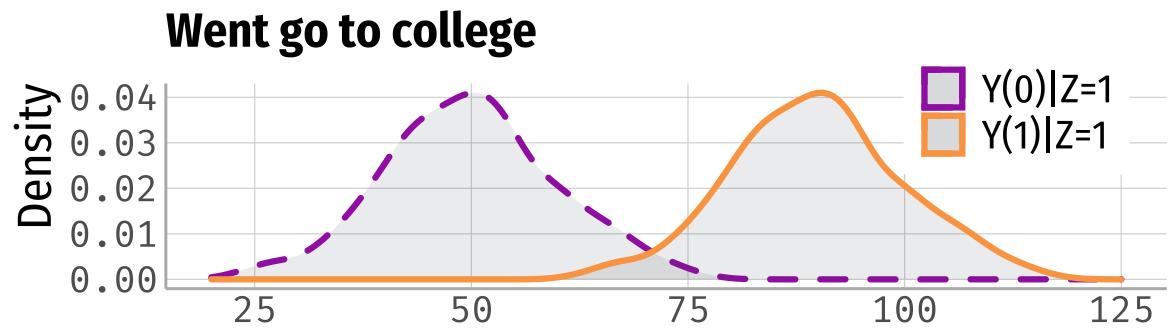
$Income(0), Income(1) \perp\!\!\!\perp College$



# What about if the ignorability assumption doesn't hold?

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

E.g. Individuals that can take  
**more advantage from college**  
**(in terms of income)** are more  
likely to go.



# Randomized Controlled Trials

- RCTs make the **ignorability assumption hold by design**

How?



# What does randomization buy us?

- Groups will be comparable **in expectation** in terms of their observable and unobservable characteristics.
- Are **unbalances** a problem?
  - Check magnitude and how many significant differences we have!
- Always conduct **robustness checks!**
  - Run simple regression (e.g.  $Y \sim Z$ ) and then add covariates.

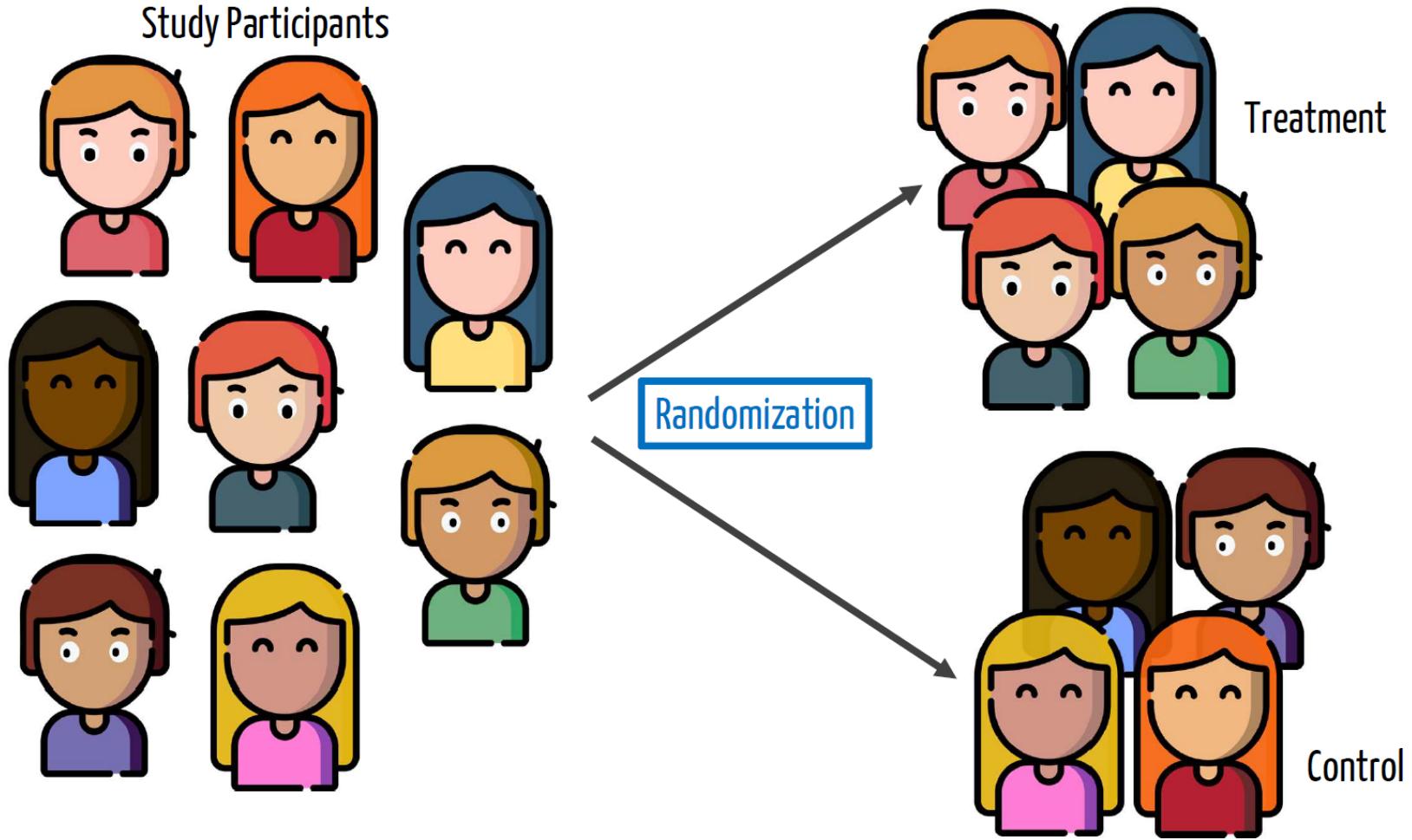
# Can we ensure balance?

- In RCTs, in general, you can't ensure balance on all covariates.
- But you can **stratify**!
- Stratification means dividing your data into different stratas or groups  $S$ , based on one or more covariates.
- Then, you randomize in the same way *within strata*.

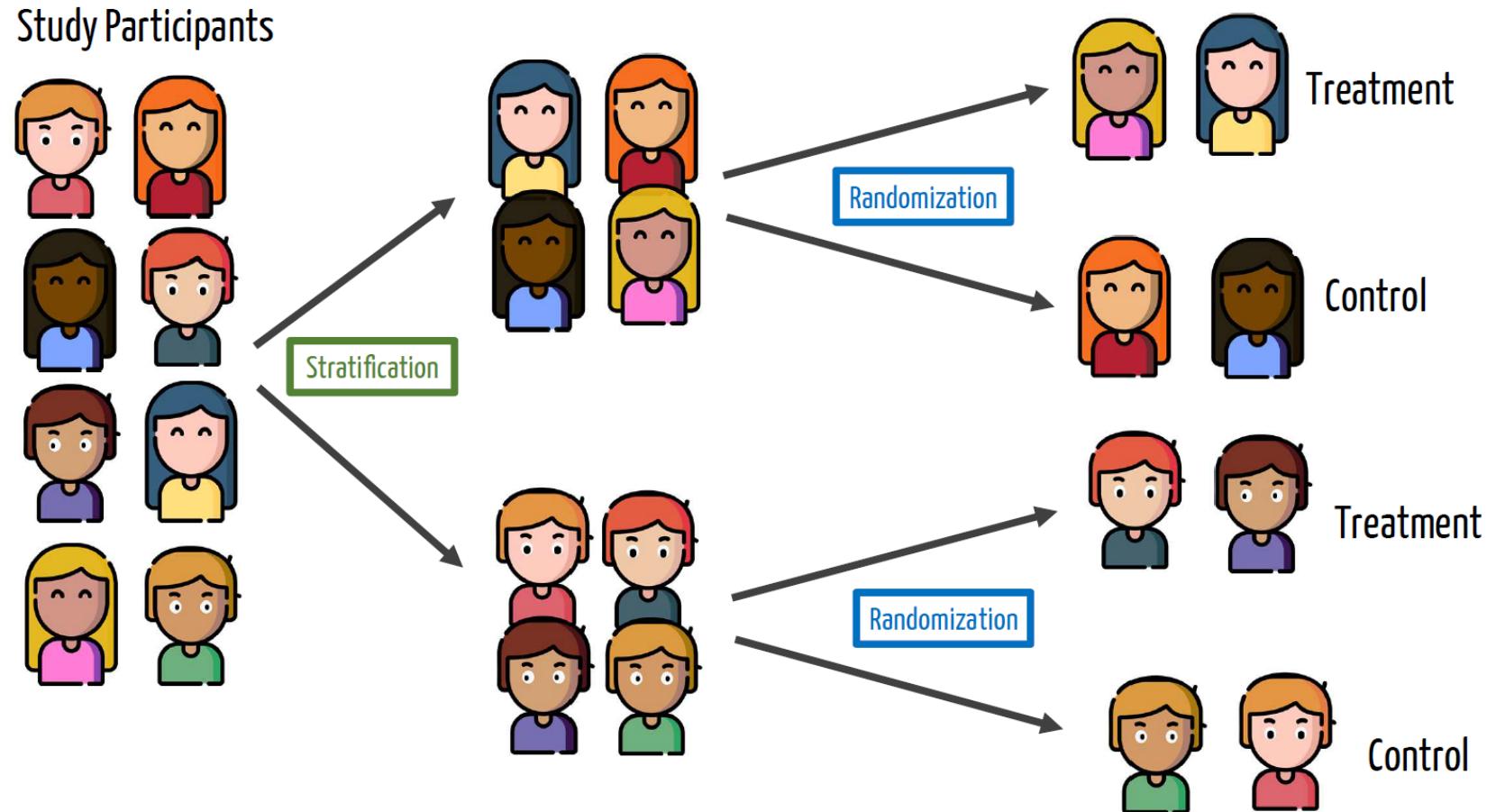
# Randomization of treatment



# Randomization of treatment with no strata



# Randomization of treatment with strata



# Get Out The Vote

- "Get out the Vote" Large-Scale Mobilization experiment (Arceneaux, Gerber, and Green, 2006)
  - "Households containing one or two registered voters where **randomly assigned** to treatment or control groups"
  - Treatment: GOTV phone calls
  - Stratified RCT: Two states divided into competitive and noncompetitive



# Checking for balance

## Balance Table by Stratum

	Non-competitive		Competitive		Non-competitive		Competitive	
	Treat	Control	Treat	Control	Treat	Control	Treat	Control
female2	0.552	0.546	0.541	0.535	0.549	0.545	0.543	0.541
fem_miss	0	0	0	0	0.026	0.025	0.022	0.021
age	52.157	51.977	50.81	50.862	55.795	55.782	53.481	53.464
newreg	0.117	0.116	0.133	0.134	0.048	0.049	0.048	0.046
persons	1.496	1.497	1.513	1.518	1.539	1.538	1.529	1.533
vote98	0.231	0.227	0.258	0.259	0.572	0.574	0.599	0.594
vote00	0.564	0.567	0.595	0.593	0.734	0.732	0.781	0.78

Let's go to R

# Estimating the effect

- Depending on the design, usually you can **compare group means** or fit a **simple regression**

$$\frac{1}{N_T} \sum_{i \in T} Y_i - \frac{1}{N_C} \sum_{i \in C} Y_i$$

$$Y_i = \beta_0 + \beta_1 Z_i + \varepsilon_i$$

How do we incorporate stratification here?

# Estimating the effect

- In stratified RCTs, we need to consider the strata!
- Run a regression with *fixed effects by strata*

$$Y_i = \beta_0 + \beta_1 Z_i + \gamma_s + \varepsilon_i$$

# Estimating the effect

```
library(estimatr)

d_s1 <- d_s1 %>% mutate(strata = interaction(state, competitiv))
summary(lm_robust(vote02 ~ treat_real + strata, data = d_s1))

##
## Call:
## lm_robust(formula = vote02 ~ treat_real + strata, data = d_s1)
##
## Standard error type: HC2
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF
## (Intercept) 0.510811  0.001036 493.086 0.000e+00 0.508780 0.51284 381057
## treat_real  0.006854  0.004626   1.482 1.385e-01 -0.002213 0.01592 381057
## strata1.1  0.086655  0.003658  23.690 5.666e-124  0.079485 0.09382 381057
## strata0.2  0.048892  0.002191  22.314 3.196e-110  0.044598 0.05319 381057
## strata1.2  0.145496  0.002192   66.382 0.000e+00  0.141200 0.14979 381057
##
## Multiple R-squared:  0.01166 ,   Adjusted R-squared:  0.01165
## F-statistic: 1181 on 4 and 381057 DF,  p-value: < 2.2e-16
```

# Estimating the effect

- One important thing to note in the previous analysis is that **assignment to treatment  $\neq$  contact**

```
d_s1 %>% count(treat_real, contact)
```

```
##   treat_real contact      n
## 1          0        0 369068
## 2          1        0   6980
## 3          1        1   5014
```

Does this break the ignorability assumption?

When we assume...

# Other potential issues to have in mind

**Generalizability of our estimated effects**

- Where did we get our sample for our study from? Is it representative of a larger population?

**Spillover effects**

- Can an individual in the control group be affected by the treatment?

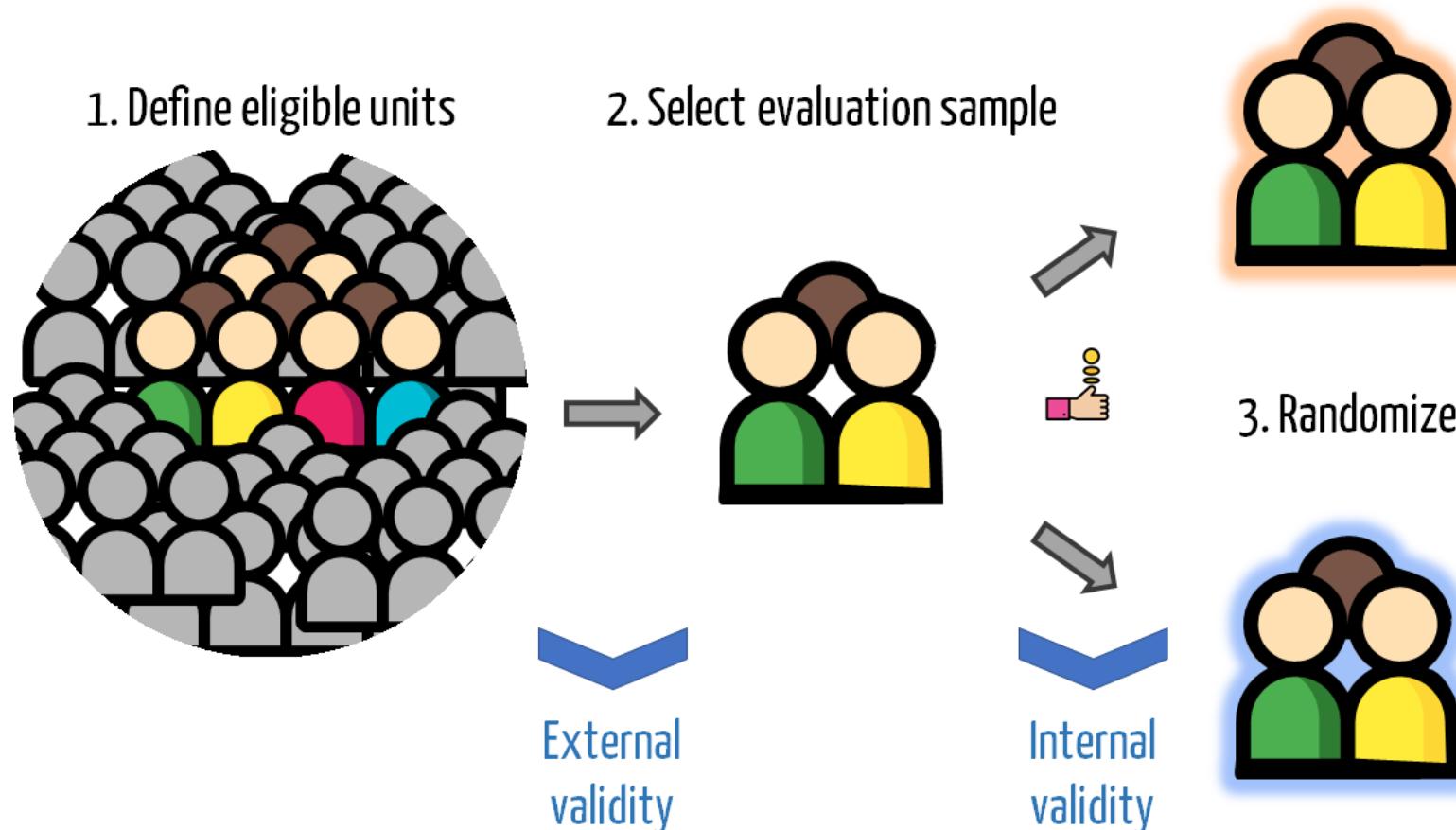
**General equilibrium effects**

- What happens if we scale up an intervention? Will the effect be the same?

# Generalizability of RCTs

- External Validity vs Internal Validity:
  - **External validity**: "The extent to which results can be generalized to other contexts or populations."
  - **Internal validity**: "[T]he extent to which the observed results represent the truth in the population we are studying."

# External vs Internal Validity



- Many times, RCTs use **convenience samples**

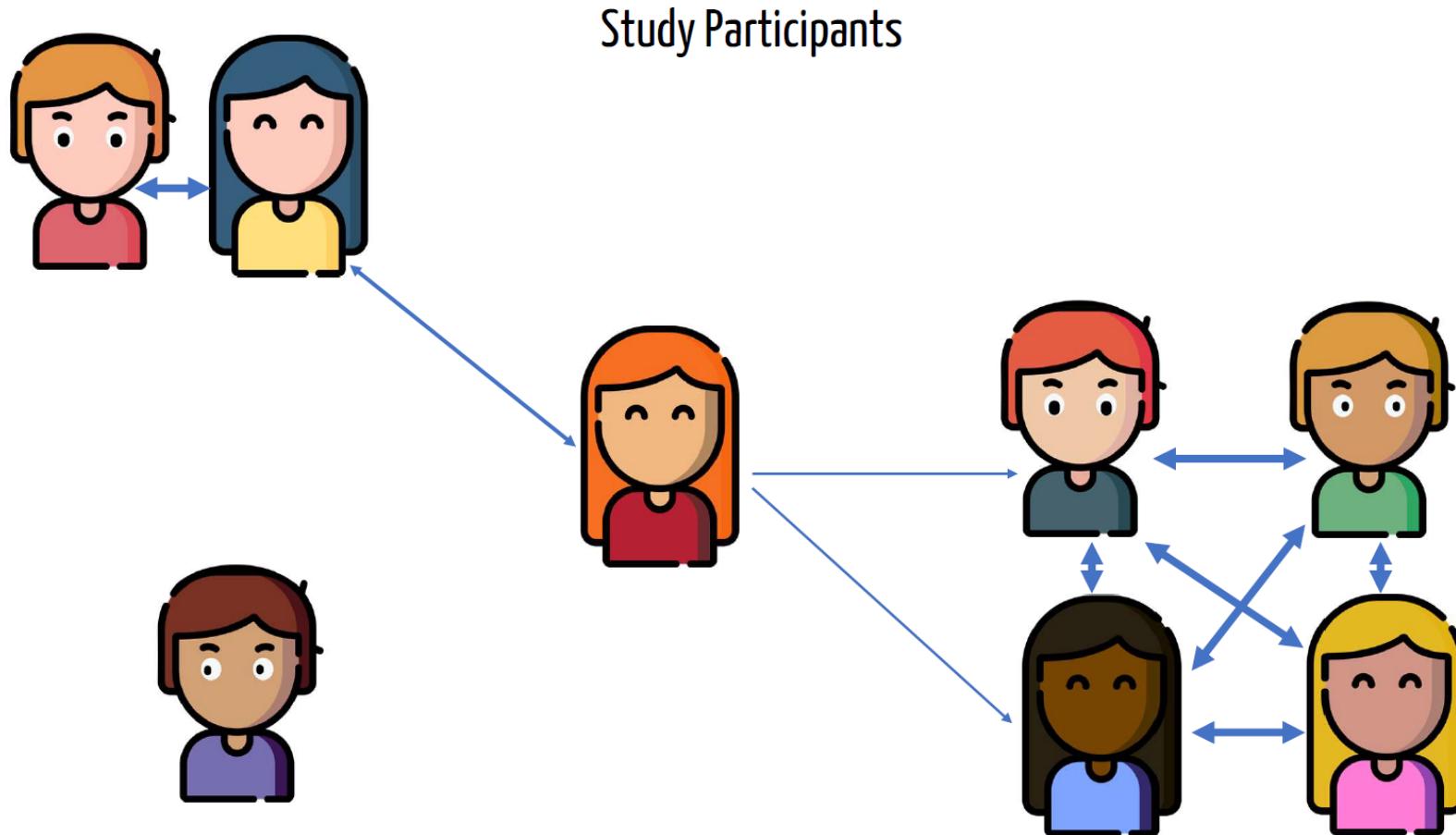
# SUTVA: No interference

- Aside from **ignorability**, RCTs rely on the **Stable Unit Treatment Value Assumption (SUTVA)**

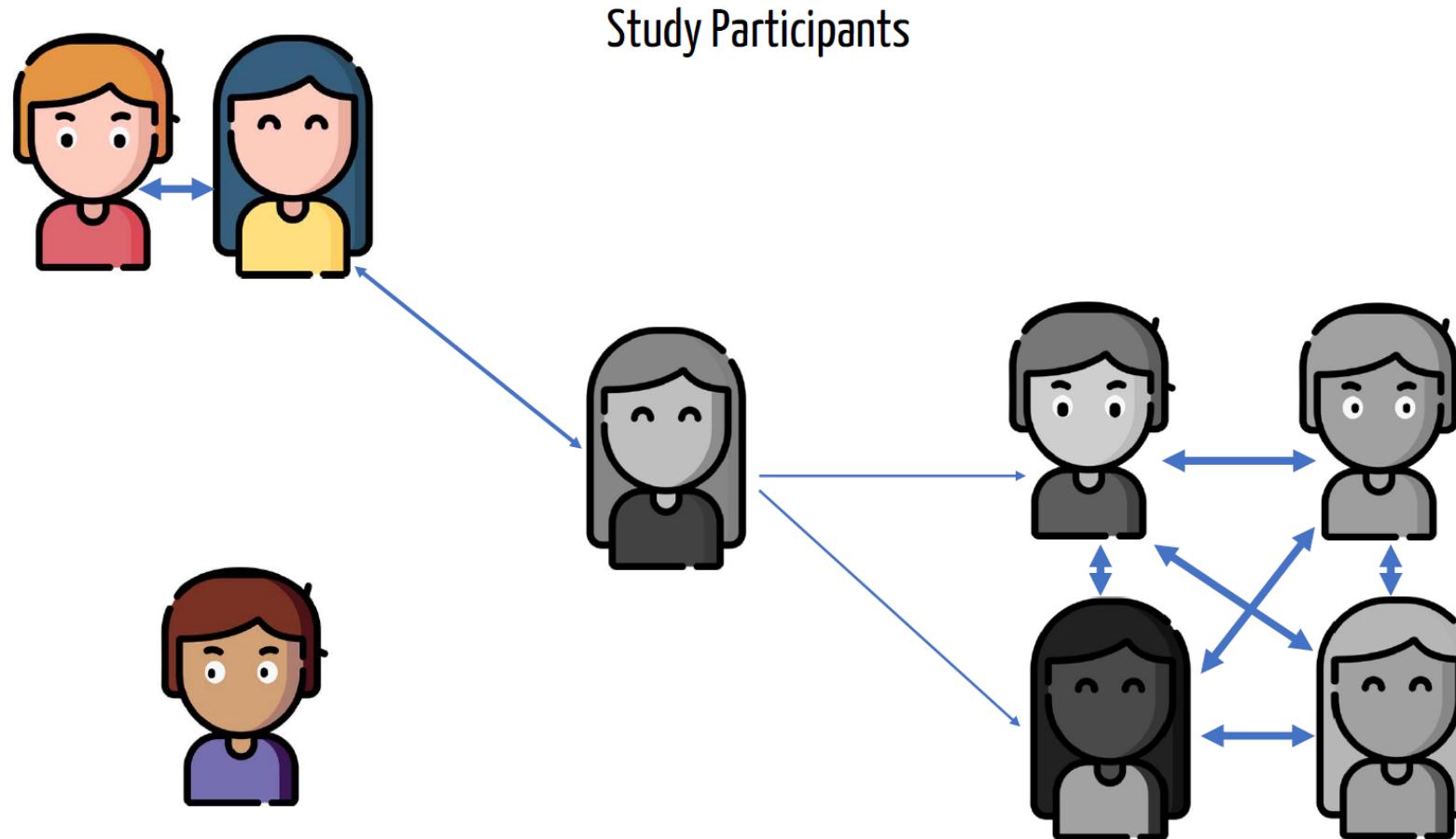
**"The treatment applied to one unit does not affect the outcome for other units"**

- No **spillovers**
- No **general equilibrium effects**

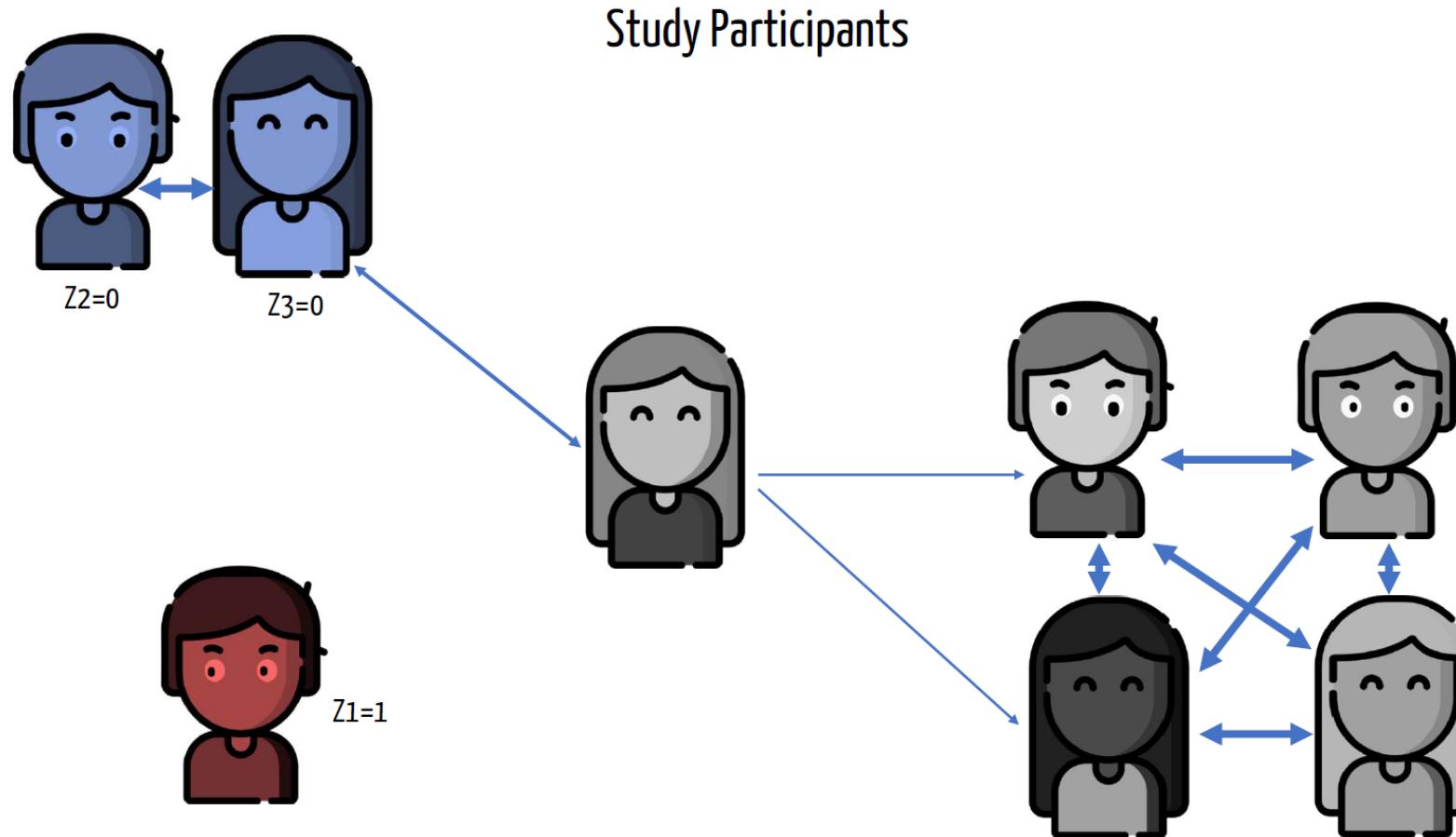
# Network effects



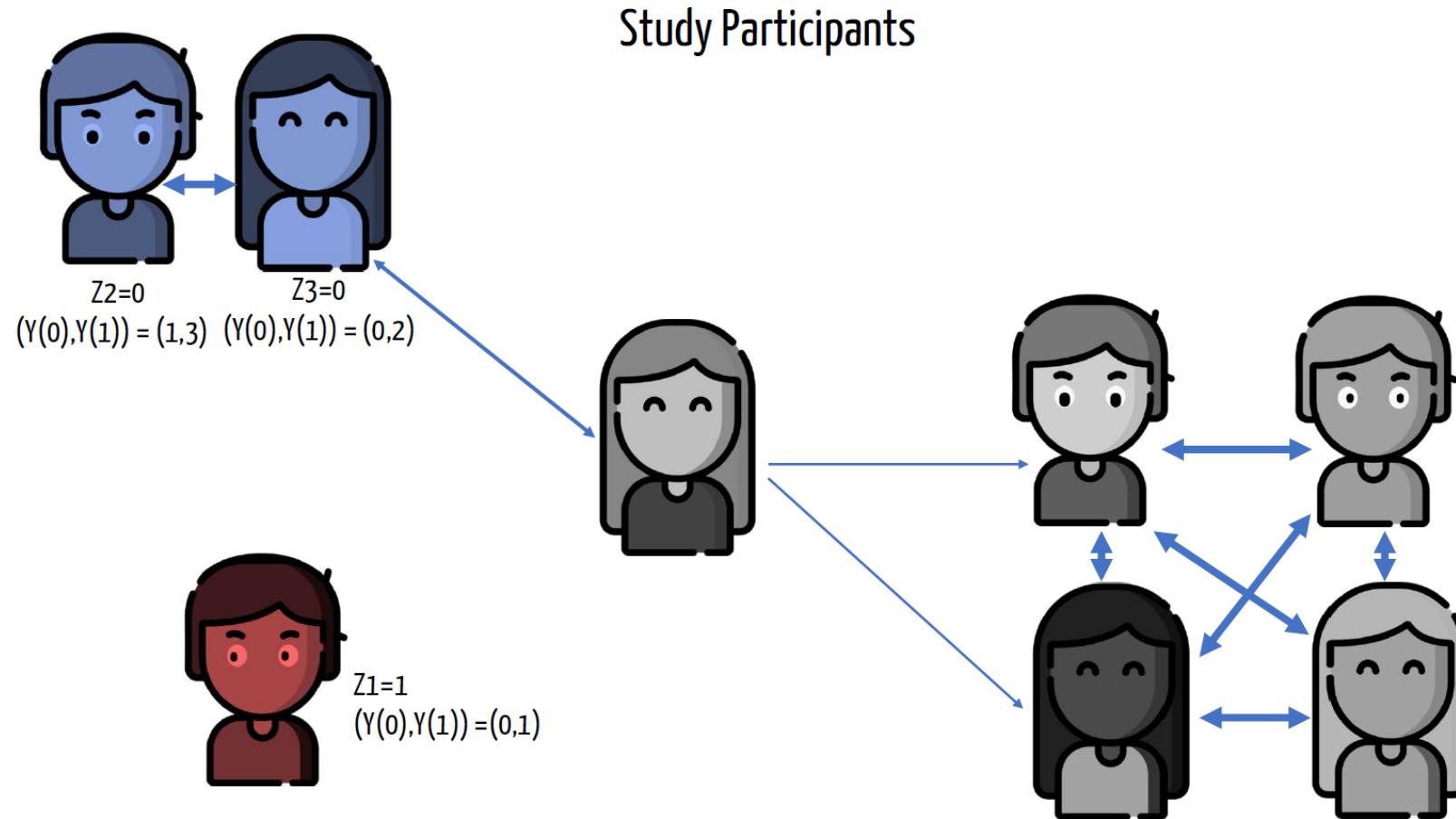
# Network effects



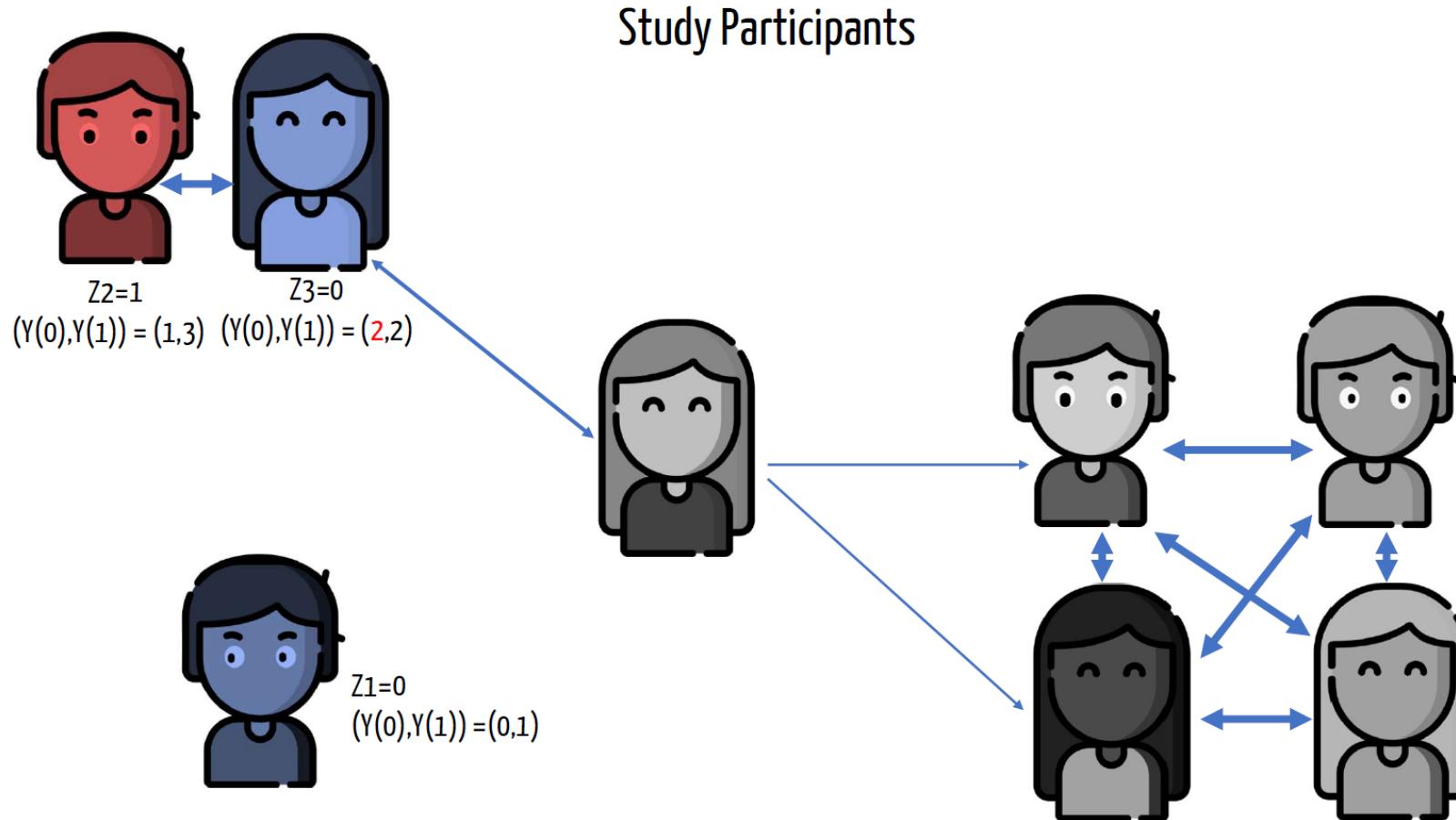
# Network effects



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# Network effects

Can we do something about this?

1. **Randomize at a higher level** (e.g. neighborhood, school, etc. instead of at the individual level)
  - Note that you will have to **cluster your standard errors**
2. **Model the network!**

# General Equilibrium Effects

- Usually arise when you **scale up** a program or intervention.
- Imagine you want to test the effect of providing information about employment and expected income to students to see whether it affect their choice of university and/or major.

**What could happen if you offer it to everyone?**

# Wrapping things up

- Randomized controlled trials are great... **but not for everything!**
- Randomization buys us **no systematic selection on observables or unobservables**
  - But things can go wrong, too!

**Check your assumptions and look out for potential issues!**