Homework Chapter 10

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- Define in your own words (i.e., don't just copy down what's written in the glossary) each of the following terms:

  - Conditional average treatment effect.

  The treatment effect conditional on the value of some covariate. For instance, the treatment effect of a drug for elderly people.

  - Average treatment on the treated.

  Treatment effect for those who ended up in the treatment group.

  - Average treatment on the untreated.

  Treatment effect for those who ended up in the control group.

- Provide an example of a treatment effect that you would expect to be highly heterogeneous, and explain why you think it is likely to be heterogeneous.

A popular theory in immigration research is the contact theory. The idea is that when natives have personal contact with immigrants they should reduce their negative stereotypes of immigrants. Blumer has a short paper which is often referred to as the "conflict hypothesis" in which he argues the opposite. What experiments can show is that in fact, the effect exists but it is very heterogeneous. Under some ideal circumstances of contact (e.g. immigrant and native share something salient in common), contact reduces stereotypes. However, under less-than-ideal circumstances, natives' negative stereotypes are reinforced.

- Consider the data in the table below that shows the hypothetical treatment effect of cognitive behavioral therapy on depression for six participants. For the sake of this example, the six participants represent the population of interest.

```
library(tidyverse)

###--- Construct the tibble
(tbl <-
  tribble(~ "Case" ,~ "Age" ,~ "Gender" ,~ "Effect",
"A" , 15 , "Man" , 7 ,
"B" , 40 , "Woman" , 3 ,
"C" , 30 , "Woman" , 7 ,
"D" , 20 , "Non-binary" , 8 ,
"E" , 15 , "Man" , 7 ,
"F" , 25 , "Woman" , 4))
```

```
## # A tibble: 6 x 4
##   Case    Age Gender     Effect
##   <chr> <dbl> <chr>       <dbl>
## 1 A        15 Man             7
## 2 B        40 Woman           3
## 3 C        30 Woman           7
## 4 D        20 Non-binary      8
## 5 E        15 Man             7
## 6 F        25 Woman           4
```

- What is the overall average treatment effect for the population?

```
###--- ATE
mean(tbl$Effect)
```

```
## [1] 6
```

- What is the average treatment effect for Women?

```
tbl |>
  filter(Gender == "Woman") |>
  summarise(mean_effect = mean(Effect))
```

```
## # A tibble: 1 x 1
##   mean_effect
##         <dbl>
## 1        4.67
```

- If nearly all Non-binary people get treated, and about half of all Women get treated, and we control for the differences between Women and Non-binary people, what kind of treatment effect average will we get, and what can we say about the numerical estimate we'll get?

That would be the variance-weighted average treatment effect. The estimate will represent those groups with higher variance in the treatment condition. In this case, that would be women, because cases are distributed evenly across the treatment variable, which maximizes variance.

- If we assume that, in the absence of treatment, everyone would have had the same outcome, and also only teenagers (19 or younger) ever receive treatment, and we compare treated people to control people, what kind of treatment effect average will we get, and what can we say about the numerical estimate we'll get?

```
tbl |>
  filter(Age <= 19)
```

```
## # A tibble: 2 x 4
##   Case    Age Gender Effect
##   <chr> <dbl> <chr>   <dbl>
## 1 A        15 Man         7
## 2 E        15 Man         7
```

This would be the ATT, which in this case is the same as the conditional treatment effect (for 19-year-olds or lower) because all individuals have the same baseline. The estimate will be 7 and represents the treatment effect only for the population that received the treatment.

- Give an example where the average treatment effect on the treated would be more useful to consider than the overall average treatment effect, and explain why.

In general for any situation in which it might be undesirable or unrealistic to treat the whole population. For instance, if we want to estimate the effect of a voucher program on consumption we want to know how it would affect the kinds of people that are likely to receive it. The effect of giving a voucher to Bill Gates on his spending will be 0 but we don't want to incorporate that into our treatment effect average.

- Which of the following describes the average treatment effect of assigning treatment, whether or not treatment is actually received?
  1. Local average treatment effect
  2. Average treatment on the treated
  3. **Intent-to-treat**
  4. Variance-weighted average treatment effect
- On weighted treatment effects:
  1. Describe what a variance-weighted treatment effect is

When we weigh types of cases by their variance in the treatment. Types of cases (as defined by some other variable) that are more evenly distributed into treatment and control (or across levels of treatment if we have a continuous treatment) receive more weight. Groups with no variance receive 0 weight.

2. Describe what a distribution-weighted treatment effect is

It's the result of matching/weighting observations in the control group to resemble the treated units along a set of covariates creating back doors. What we aim to obtain is conditional independence of receiving treatment from the outcome conditional on those covariates.

3. Under what conditions/research designs would we get each of these?

Both of these are ways to get treatment effects from observational data.

- Suppose you are conducting an experiment to see whether pricing cookies at $1.99 versus $2 affects the decision to purchase the cookies. The population of interest is all adults in the United States. You recruit people from your university to participate and randomize them to either see cookies priced at $1.99 or $2, then write down whether they purchased cookies. What kind of average treatment effect can you identify from this experiment?

Because the population of interest and your sample are different in systematic ways, you can identify the ATT, but not the ATE.

- For each of the following identification strategies, what kind of treatment effect(s) is most likely to be identified?
  1. A randomized experiment using a representative sample **ATE**

2. True randomization within only a certain demographic group **Treatment effect conditional on being part of that demographic group.**
3. Closing back door paths connected to variation in treatment **variance-weighted treatment effect**
4. Isolating the part of the variation in the treatment variable that is driven by an exogenous variable **LATE**
5. The control group is comparable to the treatment group, but treatment effects may be different across these groups. **ATT? Not sure about this one.**