### Stratification and Standardization

INFO/STSCI/ILRST 3900: Causal Inference

10 Sep 2023

### Logistics

- ► Problem Set 1 due today by 5pm
- ▶ Peer reviews assigned via Canvas Thursday (9/12) @ 12pm and due Tuesday (9/17) @ 5pm
- Post questions on Ed Discussion or come to office hours!

► Filippo: Mon 11am-12pm (Comstock 1187)

► Sam: **Tue** 4-5pm (Comstock 1187)

► Shira: Wed 3-4pm 5:30-6:30pm (Comstock 1187)

► Mayleen: **Thu** 10:15-11:15am 11am-12pm (Rhodes 657)

► After class, read 2.4 of Hernán & Robins

### Learning goals for today

At the end of class, you will be able to:

- 1. Explain marginal versus conditional exchangeability
- 2. Estimate the conditional average treatment effect using stratification
- 3. Estimate the average treatment effect using standardization

# Check Your Understanding: Exchangeability

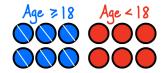
Discuss in groups, then submit your response individually to PollEverywhere. Your response won't be graded.

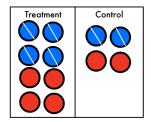
Registered voters are randomly assigned to two groups. The treatment group receives a phone call reminder to vote. The control group does not. After the election, we look at voter turnout in both groups. What does exchangeability mean in this study?

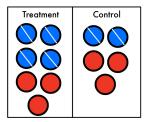


#### Review: conditional randomization

- ► Causal effect of job training on employment rate
- ► Setup 1: flip same coin for everyone
  - ► Job training with probability 2/3
- ► Setup 2: flip different coins depending on age
  - ▶ Age  $\geq$  18: Job training with probability 2/3
  - ► Age < 18: Job training with probability 1/2

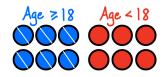


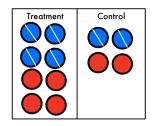


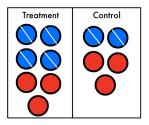


#### Review: conditional randomization

- ▶ Marginal exchangeability:  $Y^a \perp A$  for all a
- ► Suppose we find there is a treatment effect using the second setup. What is suspicious about that result?
- ► In practice, one way to reason about exchangeability is balance across covariates

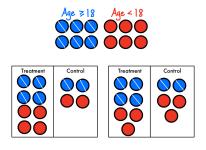




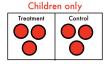


#### Review: conditional randomization

- ▶ Conditional exchangeability:  $Y^a \perp A \mid L$  for all a
- ► When we look within sub-populations, or *strata*, marginal exchangeability holds







# Check-in: Marginal vs Conditional Exchangeability

- ▶ Marginal exchangeability:  $Y^a \perp A$  for all a
- ▶ Conditional exchangeability:  $Y^a \perp A \mid L$  for all a

The potential outcomes are independent of treatment **conditional on** L (e.g. L could be an indicator of age group)

- ► How do you feel about marginal versus conditional exchangeability (thumbs up or thumbs down)?
- ► What questions do you have?

#### Stratification

- Exchangeability holds within each sub-population
- ► **Stratification**: We can directly estimate causal effect within each sub-population (or stratum)
- ► The Conditional Average Treatment Effect (CATE)

$$CATE = E(Y^{a=1} \mid L = \ell) - E(Y^{a=0} \mid L = \ell)$$

► Conditional exchangeability (+ consistency) lets us estimate expected potential outcomes from observable averages

$$\mathsf{E}(Y \mid A = a, L = \ell) \stackrel{\mathsf{consis}}{=} \mathsf{E}(Y^a \mid A = a, L = \ell)$$

$$\stackrel{\mathsf{exchange}}{=} \mathsf{E}(Y^a \mid L = \ell)$$

► If the treatment effect varies across sub-population, we say there is **treatment effect heterogeneity** 

#### Stratification

- ► Estimate the Conditional Average Treatment Effect (CATE)
- ►  $CATE = E(Y^{a=1} \mid L = \ell) E(Y^{a=0} \mid L = \ell)$
- ► Example: medication
- ► Sometimes we do need the Average Treatment Effect (ATE)
- ►  $ATE = E(Y^{a=1}) E(Y^{a=0})$
- Example: new feature on YouTube (two thumbs up)
- ► How can we go from CATE to ATE?
- ► Law of Total Expectation:

$$E[Y^a] = \sum_{\ell} E[Y^a \mid L = \ell] \cdot Pr(L = \ell)$$

#### Standardization

- ► **Standardization** allows us to estimate the ATE by combining estimates from each sub-population
- ▶ For L = 0, 1

$$E(Y^{a}) = E(Y^{a} \mid L = 1) \cdot Pr(L = 1) + E(Y^{a} \mid L = 0) \cdot Pr(L = 0)$$

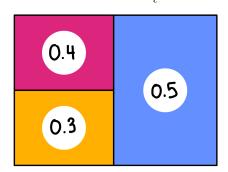
$$= E(Y \mid L = 1, A = a) \cdot Pr(L = 1) + E(Y \mid L = 0, A = a) \cdot Pr(L = 0)$$

► More generally, for each *a* 

$$\mathsf{E}(Y^a) = \sum_{\ell} \mathsf{E}(Y \mid L = \ell, A = a) \cdot \mathsf{Pr}(L = \ell)$$

### Standardization

$$\mathsf{E}(Y^a) = \sum_{\ell} \mathsf{E}(Y \mid L = \ell, A = a) Pr(L = \ell)$$



# Check Your Understanding: Standardization

$$\begin{aligned} \mathsf{E}(Y^{a=0}) &= \sum_{\ell} \mathsf{E}(Y \mid L = \ell, A = 0) Pr(L = \ell) \\ \mathsf{E}(Y^{a=1}) &= \sum_{\ell} \mathsf{E}(Y \mid L = \ell, A = 1) Pr(L = \ell) \end{aligned}$$

		L	Α	Υ
1	Rheia	0	0	0
2	Kronos	0	0	1
3	Demeter	0	0	0
4	Hades	0	0	0
5	Hestia	0	1	0
6	Poseidon	0	1	0
7	Hera	0	1	0
8	Zeus	0	1	1

`	,			
		L	Α	Υ
9	Artemis	1	0	1
10	Apollo	1	0	1
11	Leto	1	0	0
12	Ares	1	1	1
13	Athena	1	1	1
14	Hephaestus	1	1	1
15	Aphrodite	1	1	1
16	Polyphemus	1	1	1
17	Persephone	1	1	1
18	Hermes	1	1	0
19	Hebe	1	1	0
20	Dionysus	1	1	0

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$$Pr(L = 0) \cdot E(Y \mid L = 0, A = 0) =$$
 $Pr(L = 1) \cdot E(Y \mid L = 1, A = 1) =$ 
 $Pr(L = 0) \cdot E(Y \mid L = 0, A = 1) =$ 

 $Pr(L = 1) \cdot E(Y \mid L = 1, A = 0) =$ 

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