STA 235H - Introduction to Observational Studies I

Fall 2021

McCombs School of Business, UT Austin

Announcements

Homework 3 will be posted on Thursday

- Homework 2 answer key has been added to the course website (**check out the rubric!**)
- **No office hours today** → Moved to tomorrow (check out Calendly)
- I'll send out a poll for a **review session** for the midterm
  - If you are interested, please respond.

Last week

- Randomized controlled trials
  - Why is it considered the gold standard?
  - How to analyze an RCT in practice?
  - Assumptions and limitations.

Last week

- Randomized controlled trials
  - Assumptions for RCTs?

Last week

- Randomized controlled trials
  - Limitations?

Today, we're moving forward...

- Introduction to Observational Studies:
  - Can we identify causal effects without RCTs?
  - Assumptions
  - Matching vs OLS

No more chance[s]

Introduction to observational studies

- Most times, we will not be able to randomize, and we need to work with **existing data**

Observational data

- Data for which we can't manipulate the treatment assignment, e.g. data in its "natural state".

Can we reasonably assume that the ignorability assumption holds?

Introduction to observational studies (cont.)

- Moving away from the core assumption of RCTs: that **"the probability of treatment assignment is a known function"** (Imbens & Rubin, 2015).

Introduction to observational studies (cont.)

- Moving away from the core assumption of RCTs: that "the probability of treatment assignment is a known function" (Imbens & Rubin, 2015).
- We will maintain the assumption of unconfoundedness (to a certain extent).

What is that?

Calling in the CIA

- Unconfoundnedness means that the treatment assignment is independent from the potential outcomes.
- If you recall, the ignorability assumption assumes that:

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

- What if you could assume that this holds conditional on some covariates?

Conditional Independence Assumption (CIA)

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

An example about the CIA

- Let's think about the fake CV example and a real life application.
- Causal question: How does getting an internship affect your probability of being in the film industry 5 years later?
- A firm needs to hire interns ASAP, no time for interviews. What would this firm look at in a CV?
  - e.g. level of education, experience, name?
- *Could we assume that conditional on education, experience, name characteristics, etc. receiving an internship is independent from your potential outcomes?*

The assignment mechanism

- Key component in causal analysis:
    - In RCTs, assignment mechanism is *known*.
    - But in observational studies?

Selection on observables

- Units select into treatment based on characteristics **I can observe**.
- What this means in practice is that **all confounders are observable and I can adjust for them**.
  - **Overt bias:** Bias caused by observed confounders. I can remove it by adjusting by these variables.
  - **Hidden bias:** Bias caused by unobserved confounders. I can't directly remove it (I need to rely on other assumptions).

How do we adjust for observables?

- One way we have seen so far is **regression adjustment**

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \varepsilon_i$$

Under unconfoundedness, how would we interpret β_1?

How do we adjust for observables?

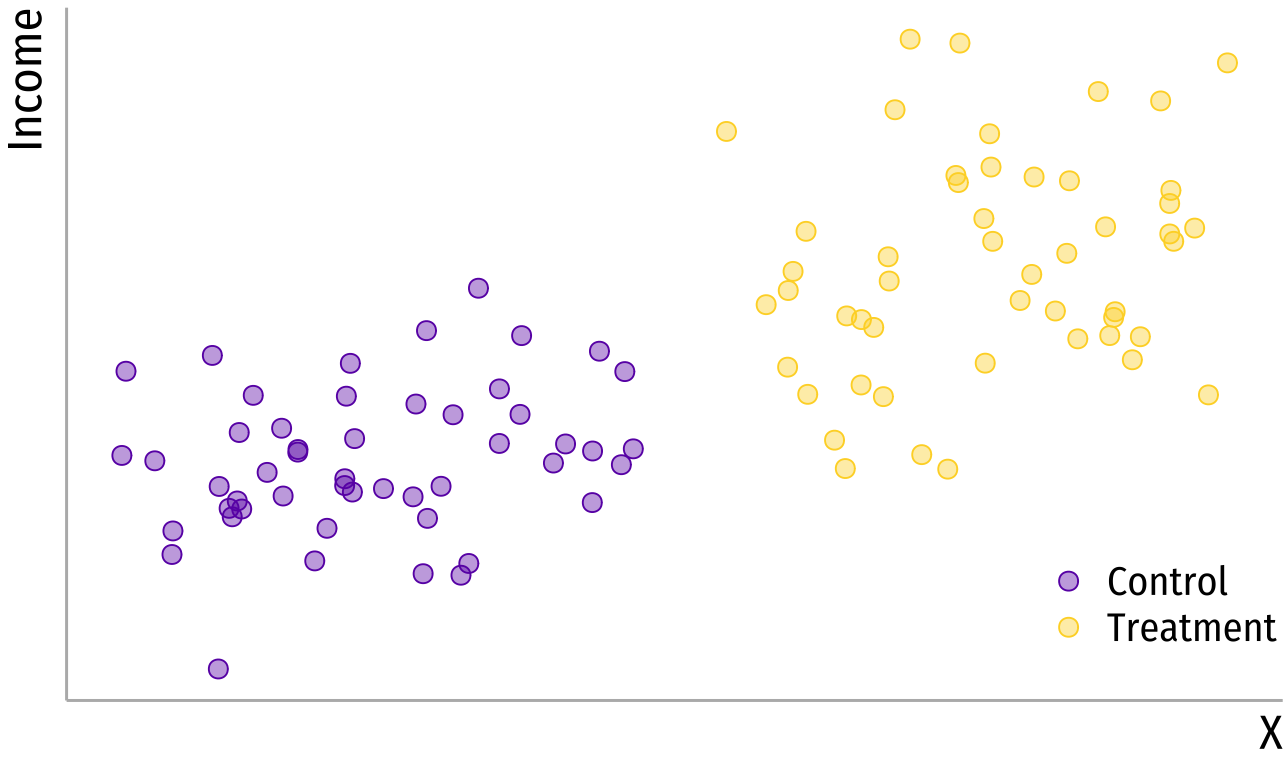
- One way we have seen so far is **regression adjustment**

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \varepsilon_i$$

β_1 is the estimated effect of Z on Y, holding X constant

How do we adjust for observables?

- But what if our data looks like this? Do you see a problem?



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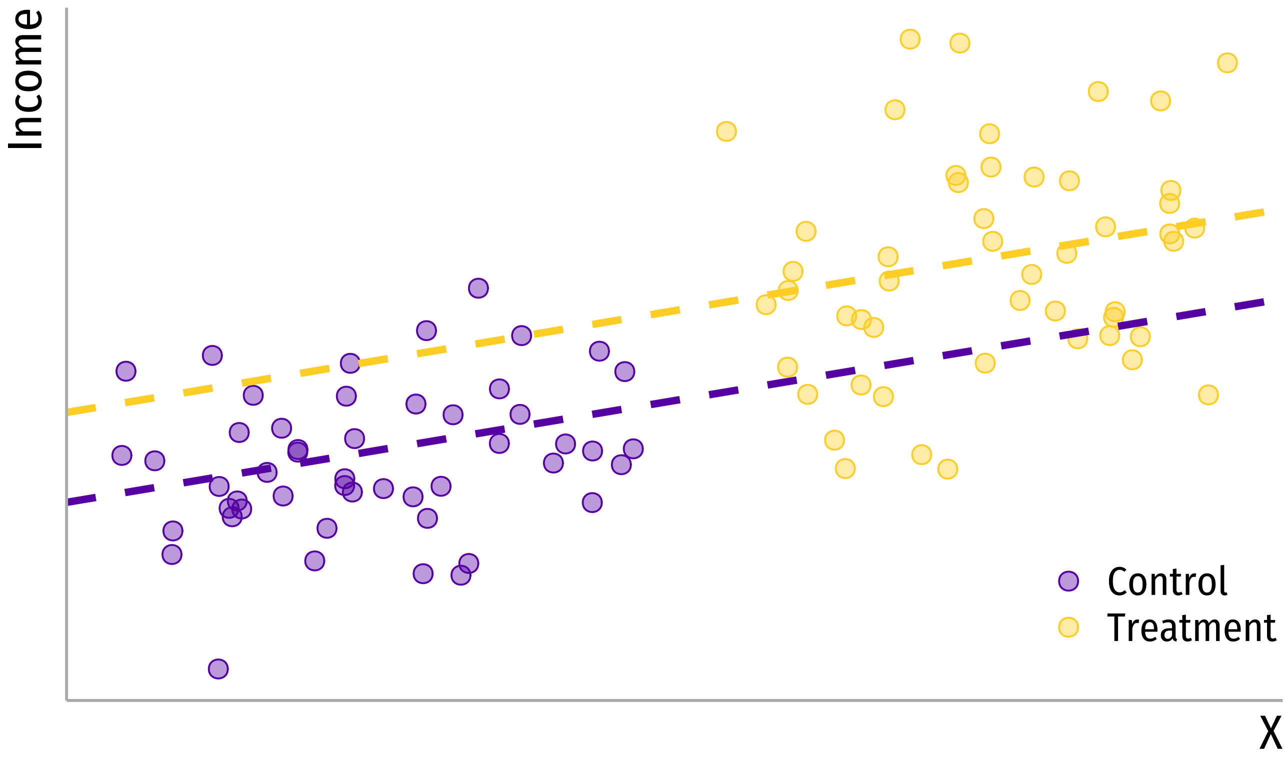

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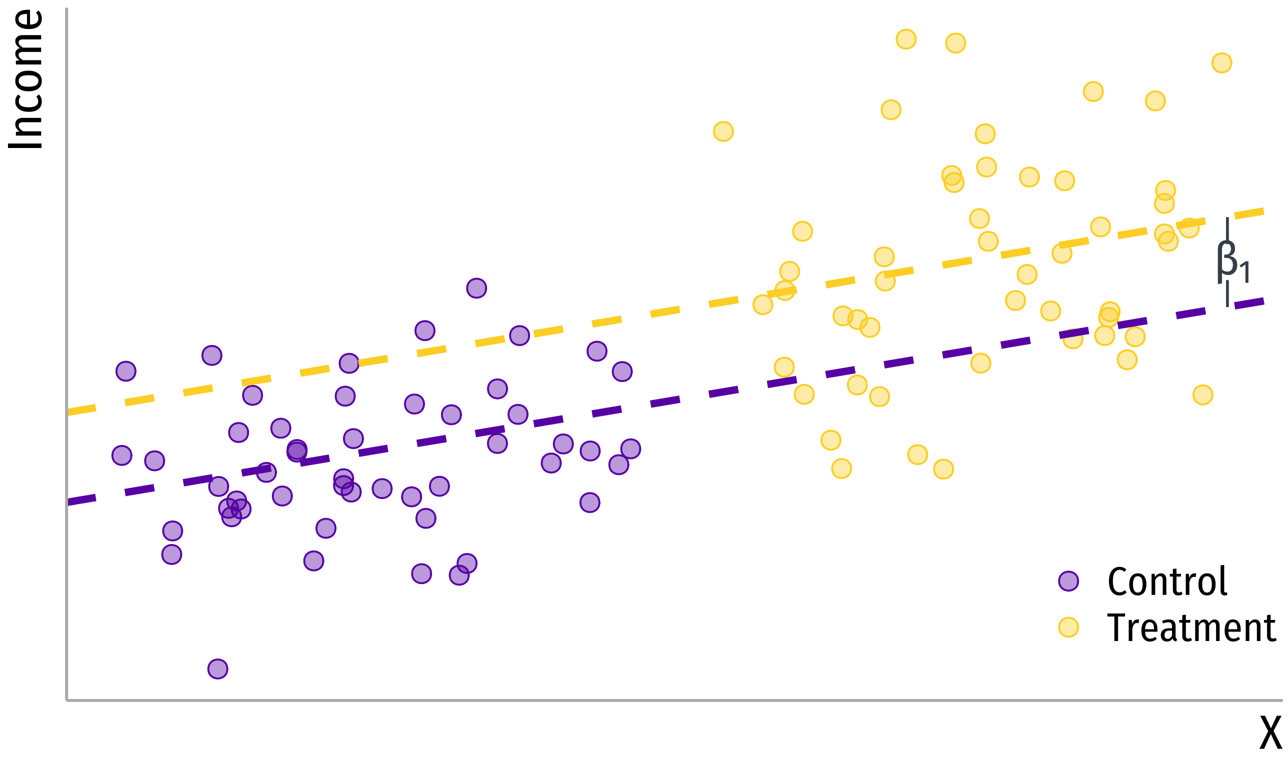

Finding your perfect match...

Two peas in a pod

- One other route we could take is to **find similar units** in our sample and **group them together**.

- There are different ways to do it:
    - E.g. subclassification, matching.

Two peas in a pod

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What do we gain?

Advantages of matching methods

Reduce model dependence

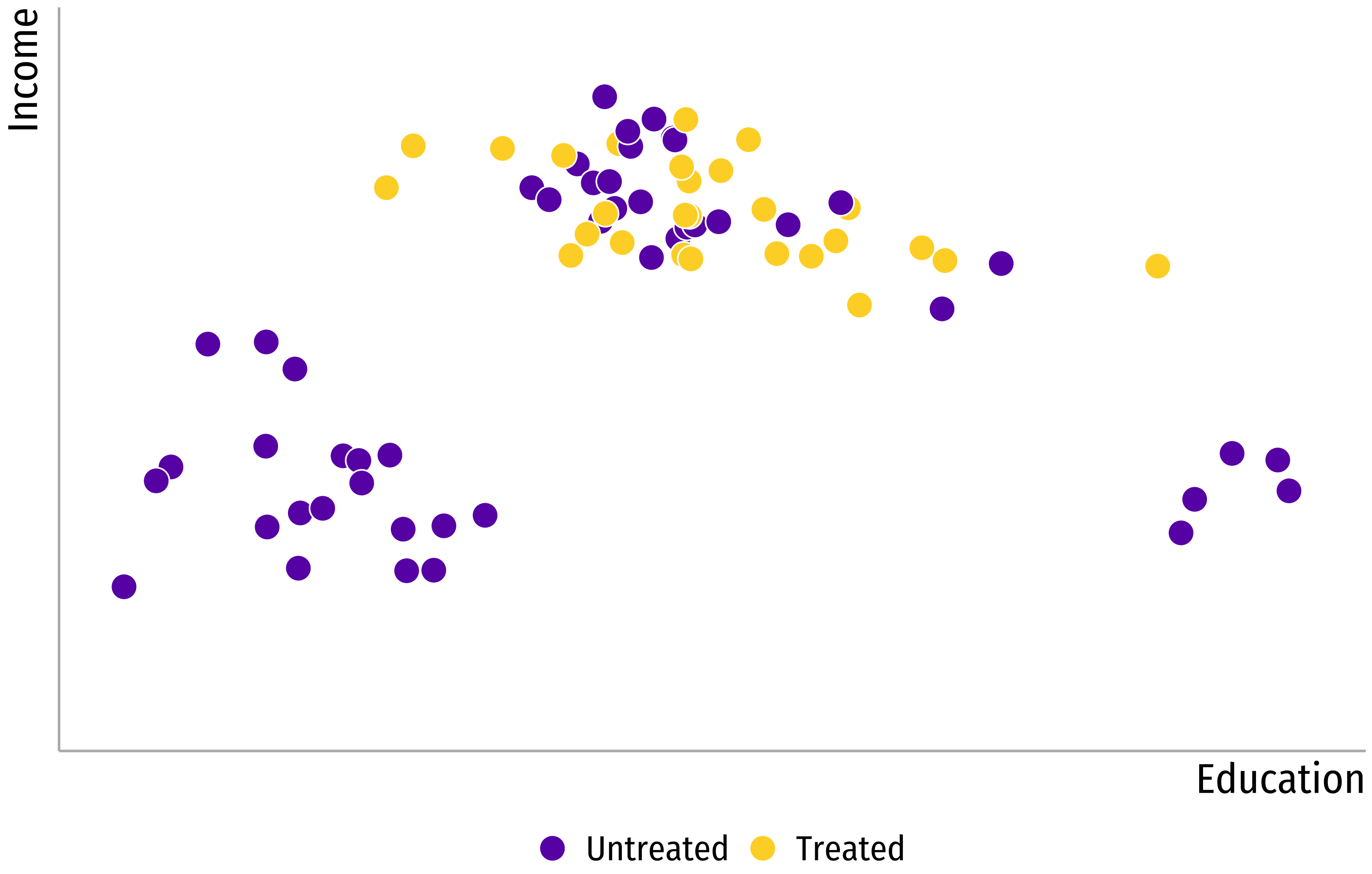
Imbalance $\longrightarrow$ model dependence $\longrightarrow$ researcher discretion $\longrightarrow$ bias

Compare like to like

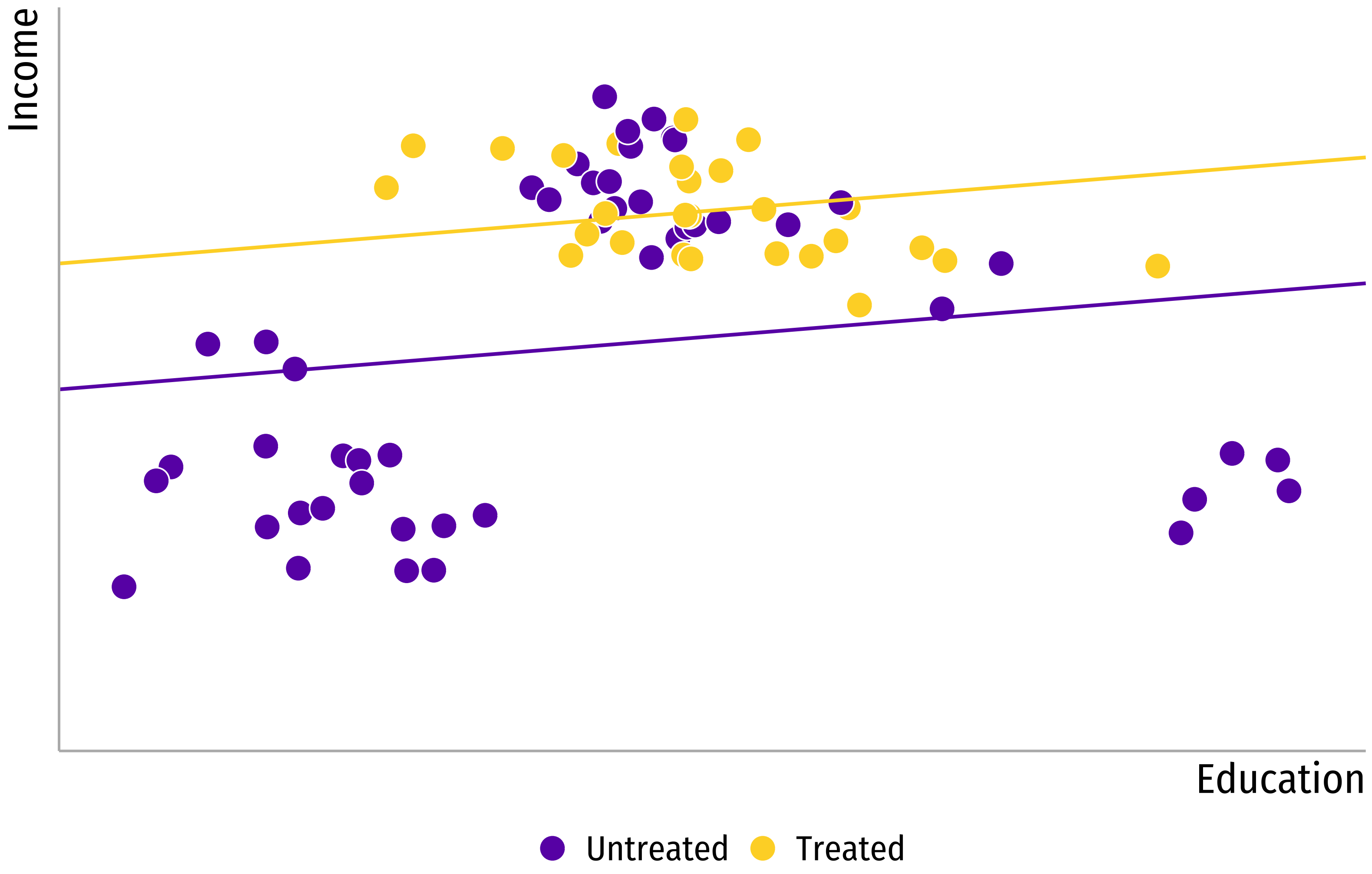
No extrapolation!

Can adjust closely by covariates

Exact matching, coarsened exact matching, fine balance..


Income
Education
Untreated
Treated

$$\text{Income} = \beta_0 + \beta_1\text{Education} + \beta_2\text{Treatment}$$



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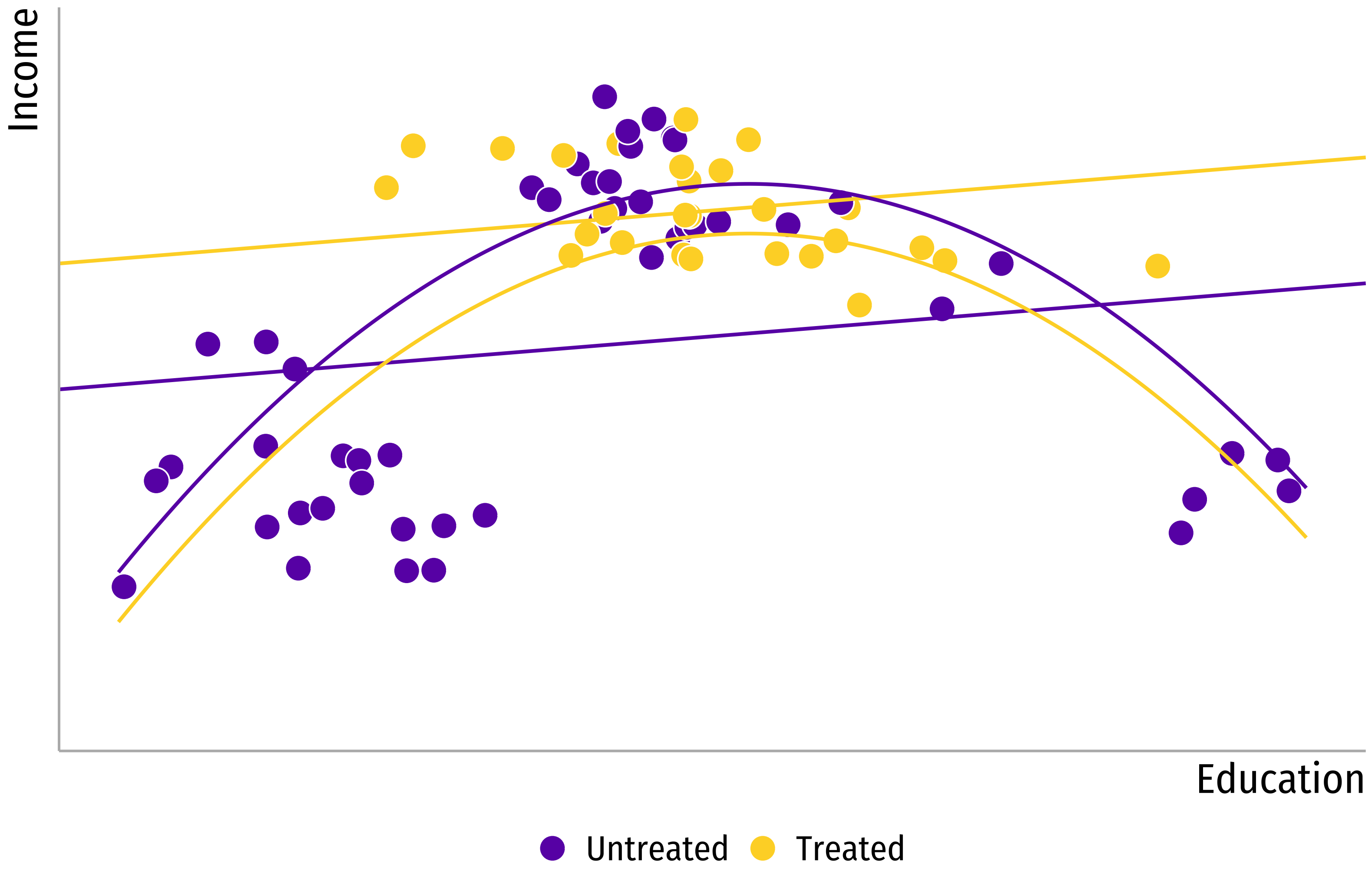

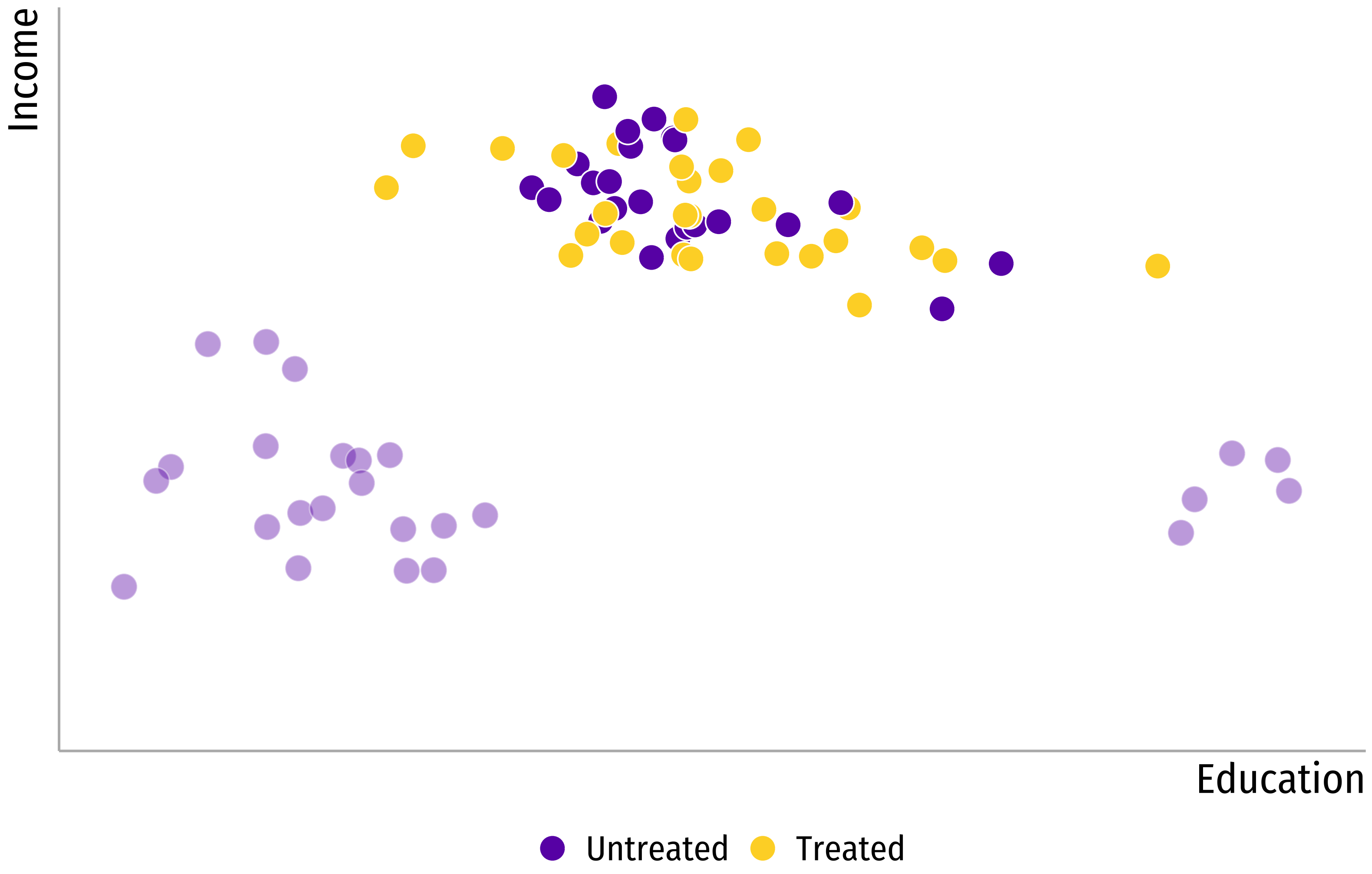
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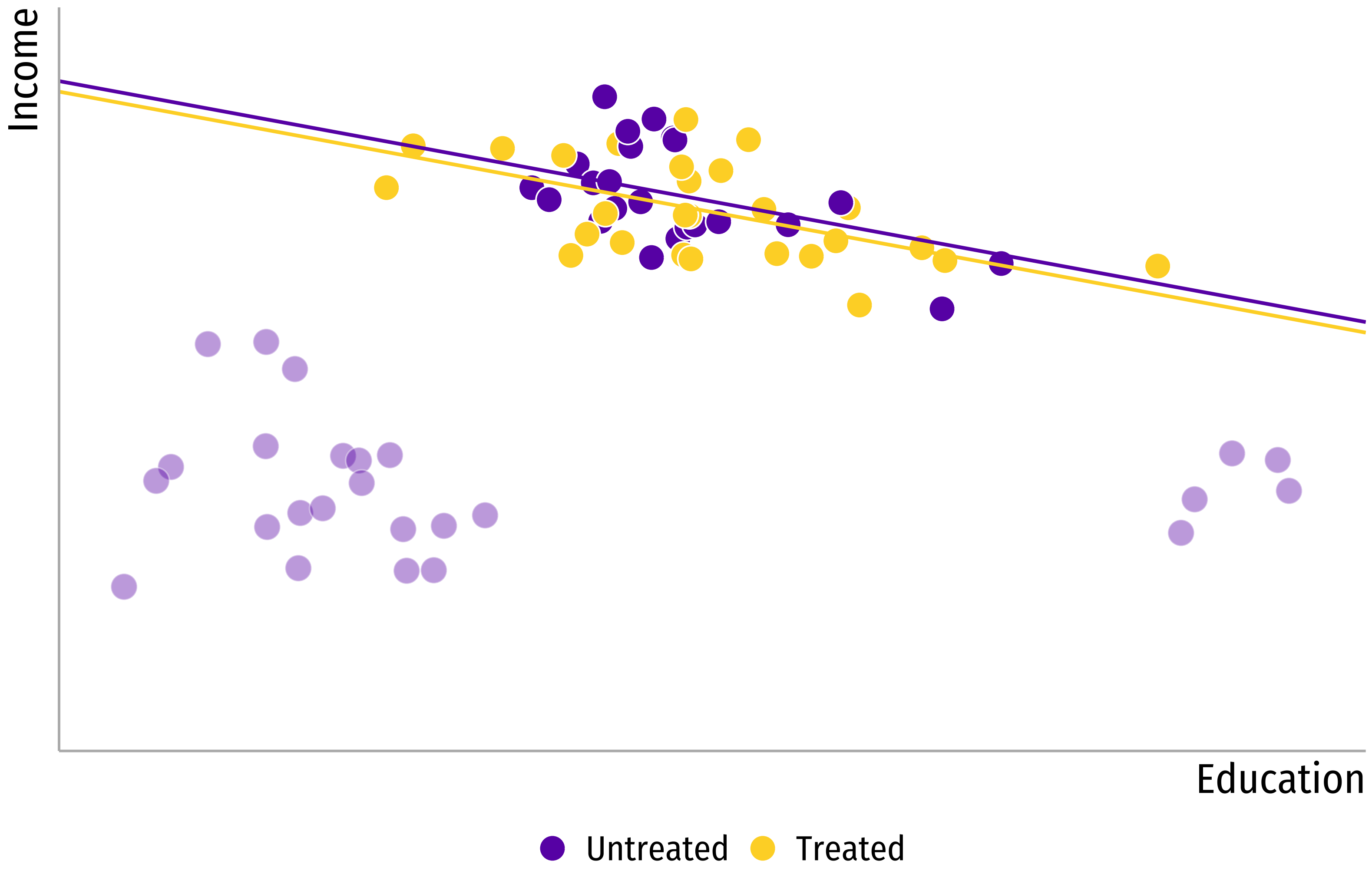

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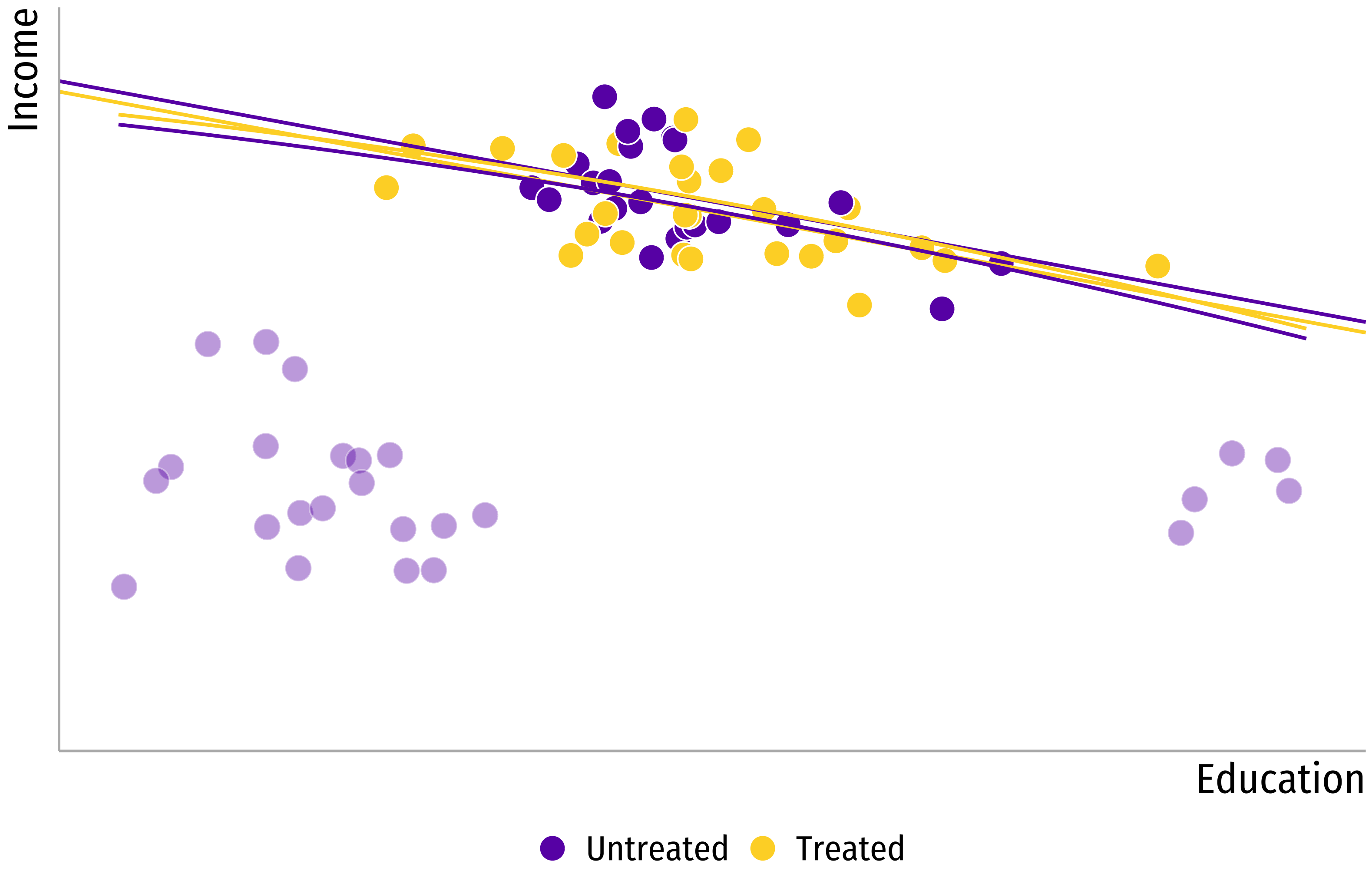
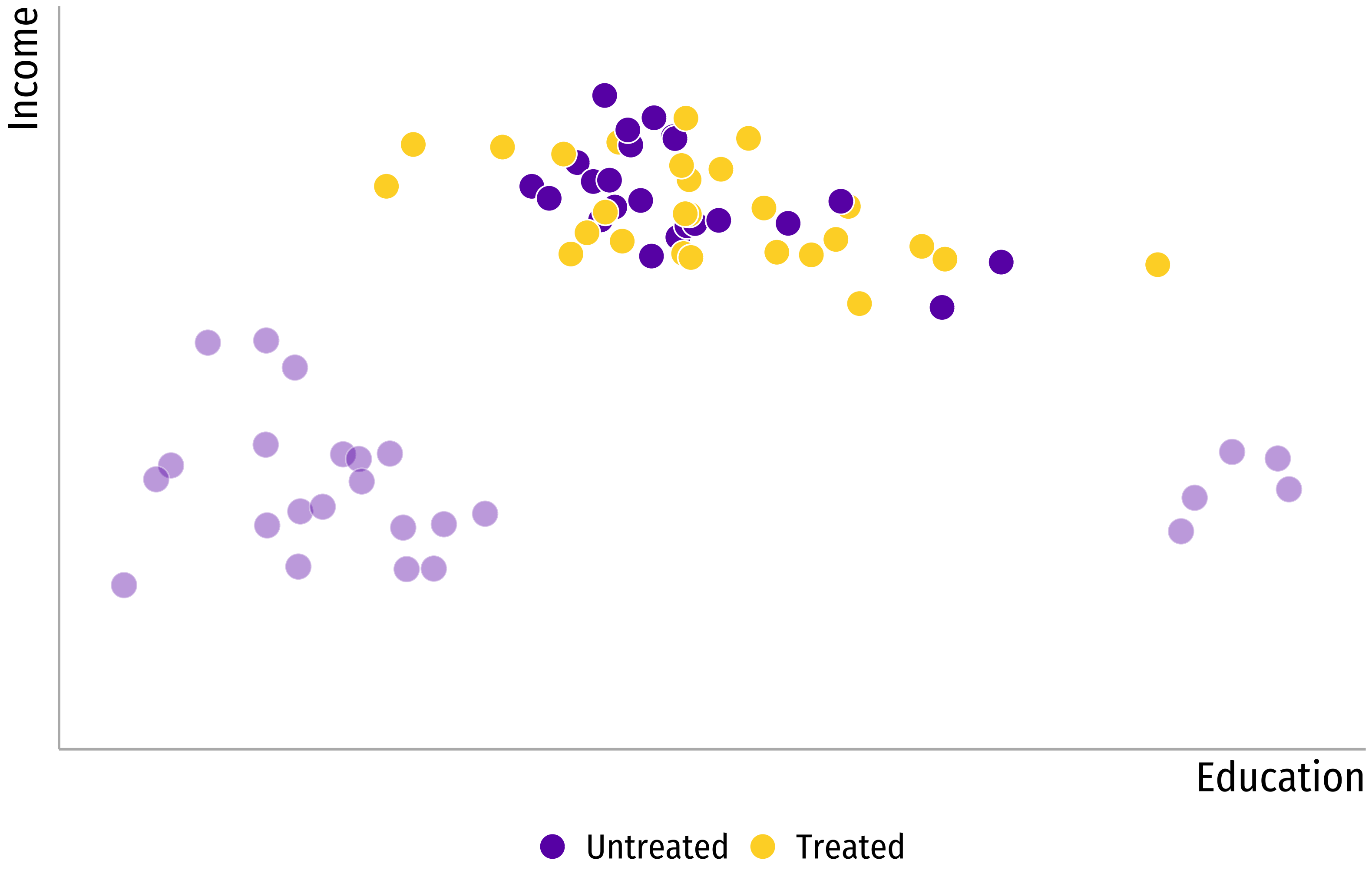
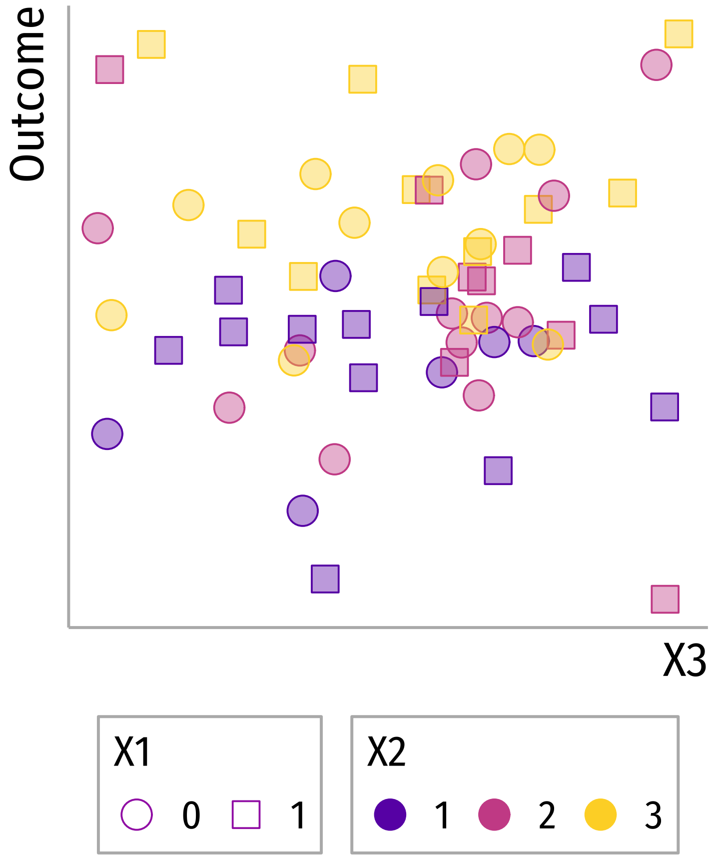


How do we know we can remove those observations?



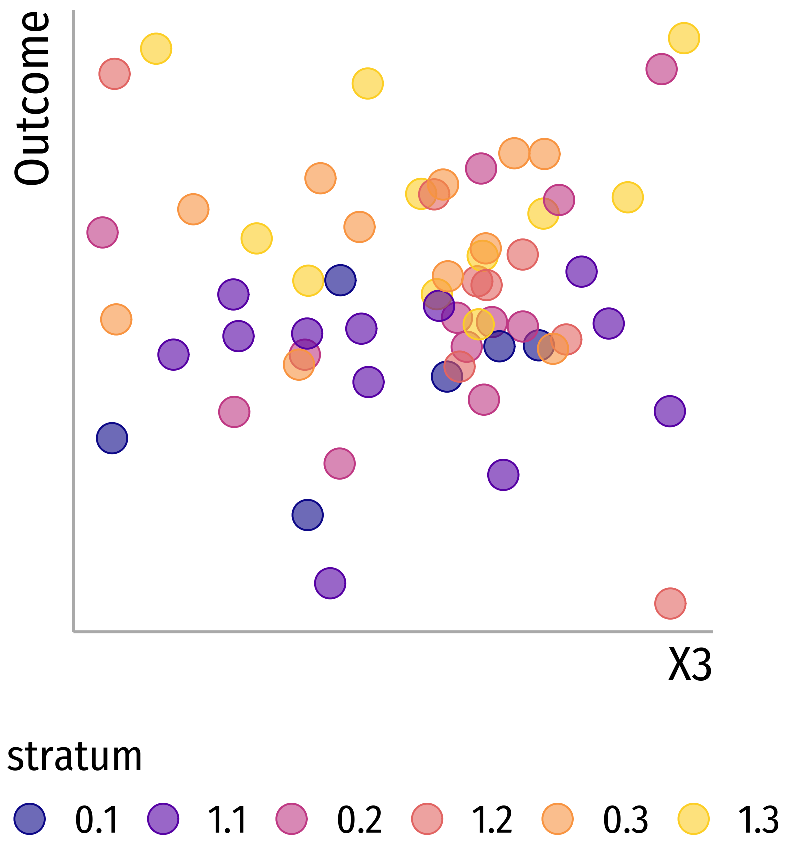
Subclassification

- Very similar to **stratifying**.



Subclassification

- Very similar to stratifying.
- Build combination of X1 and X2 (strata).



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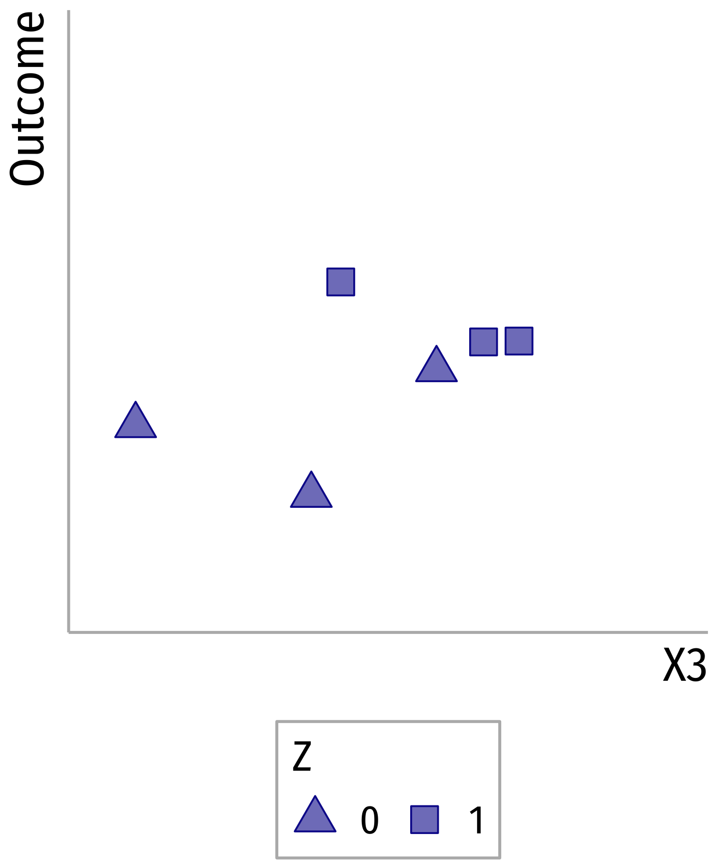

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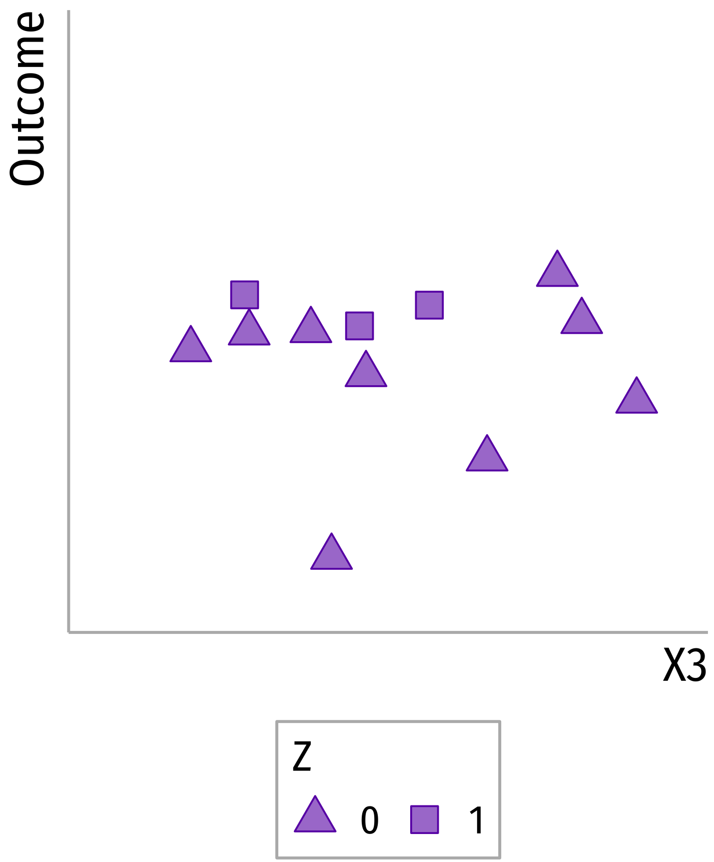

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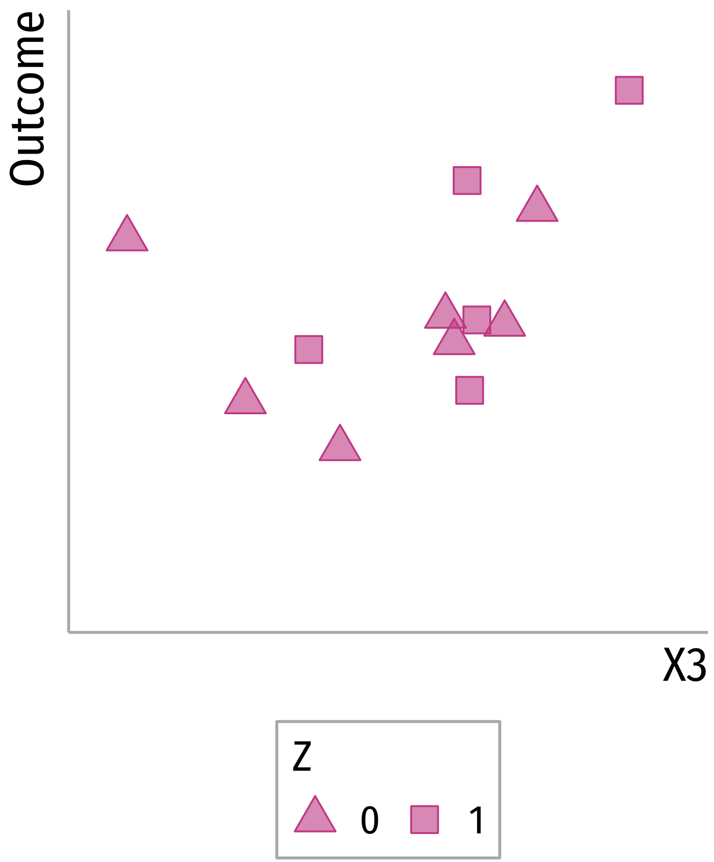

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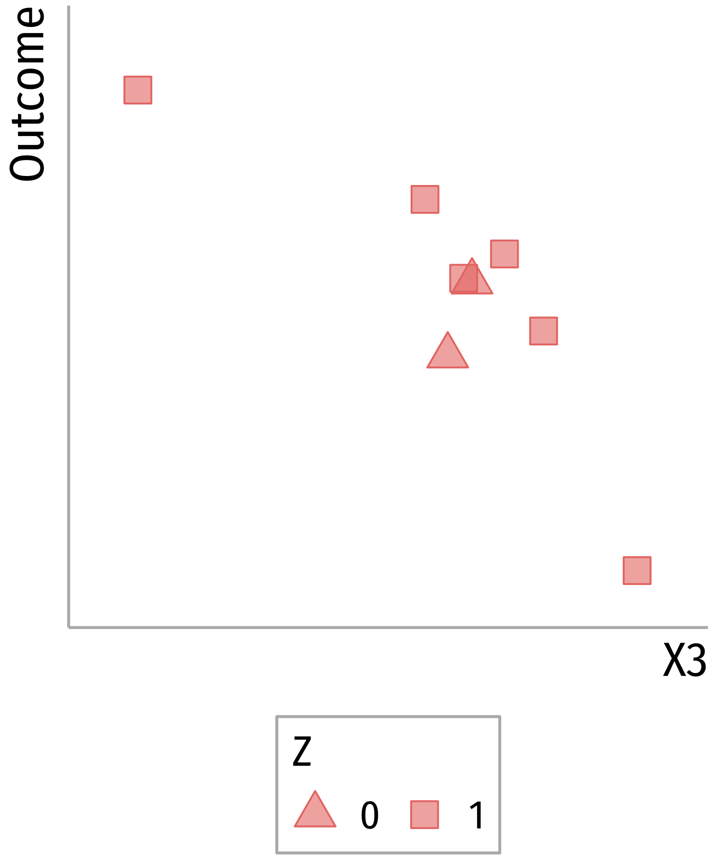

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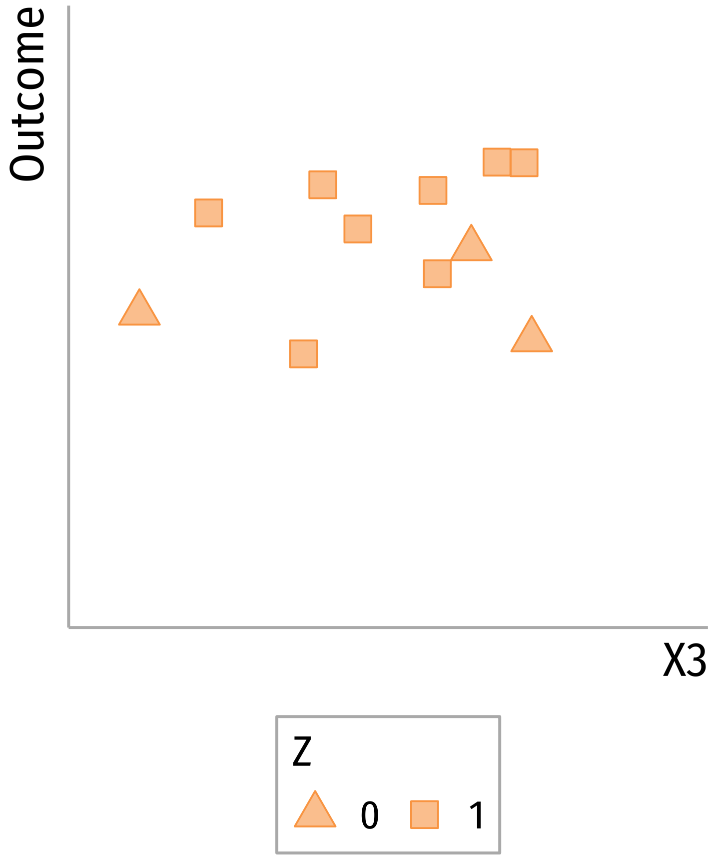

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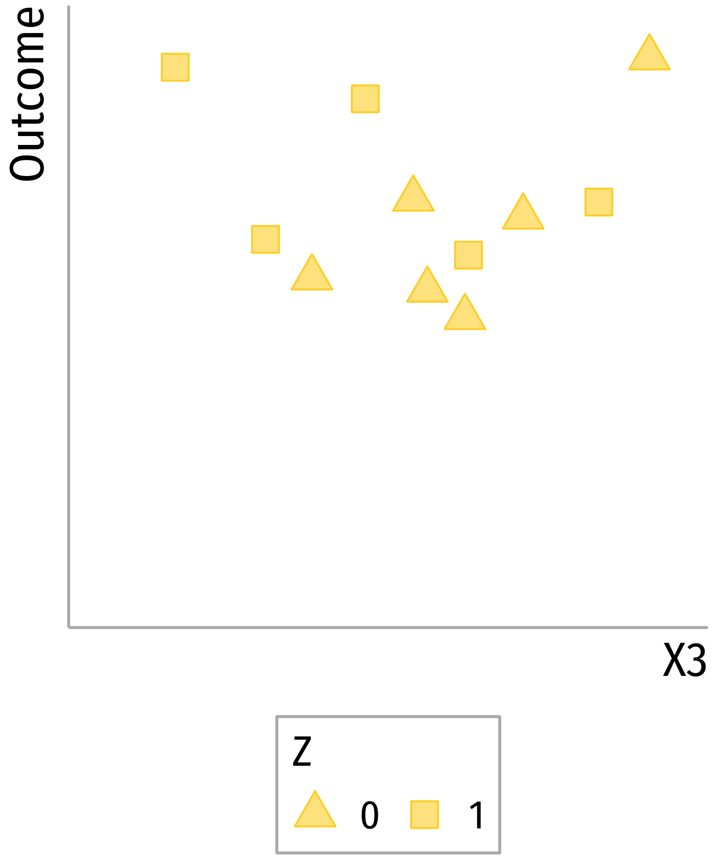

Subclassification

- To estimate the Average Treatment Effect, we take a **weighted average**:

$$\hat{ATE} = \sum_{s=1}^{S} \frac{N_s}{N} (\bar{Y}_{1s} - \bar{Y}_{0s})$$

What happens when we have too many variables to build strata?

The curse of dimentionality

- When we have too many covariates, the number of strata or groups grow exponentially!
    - E.g. with 4 covariates, each with 5 categories, we have 625 combinations!
- Very possible that a stratum only has treatment or control units.

The curse of dimentionality

- When we have too many covariates, the number of strata or groups grow **exponentially**!
    - E.g. with 4 covariates, each with 5 categories, we have **625 combinations**!
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What to do?

Breaking the curse: Balancing scores

- Want to reduce the dimentionality of our covariates

- A balancing score $b(x)$ is a function of the covariates such that:

$$Z_i \perp\!\!\!\perp X_i | b(X_i)$$

- This means that conditioning on the balancing score is enough to remove bias associated to the covariates.

- Under unconfoundedness:

$$Y_i(0), Y_i(1) \perp\!\!\!\perp Z_i | b(X_i)$$

- There are different balancing scores:
    - E.g. propensity scores, mahalanobis distance.

Estimating balancing scores

Propensity score

$$\log(\frac{p}{1-p}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon$$

where $p = Pr(Z = 1)$

```
e <- predict(glm(z ~ x1 + x2 + x3, data = d, family = binomial(link="logit")),
             type="response")
```

Estimating balancing scores

Propensity score

- Importance of overlap region

Making groups comparable

- Using the previous balancing scores (or covariates directly!) we can match observations between the treatment and control group

Step 1: Preprocessing

Try to model the treatment assignment

Step 2: Estimation

Use the new trimmed/preprocessed data to build a model, calculate difference in means, etc.

How matchy-matchy

- There are different matching methods (and different ways to use them!)

Nearest neighbor (NN)

Use balancing scores; Greedy algorithm

Optimal matching

Solves an optimization problem; slow on large samples

Mixed Integer Programming (MIP) matching

Balances covariates directly; can generate smaller samples

Let's go to R

The shortcomings of matching

- Many researchers missuse matching and confuse it with an identification strategy
- In terms of identification, matching still relies on selection on observables

You need other source of exogeneous variation!

- Claiming that you can identify a causal effect just by using matching is almost the same as claiming this using a regression approach.

Usually not a good idea...

Don't get it twisted

- Matching works great as an adjustment method.
- Combined with other identification strategies, it can improve results!

Main takeaways

- Matching methods can be great tools for your analysis.
    - Create more similar groups of comparisons.
    - Reduce model dependence
    - Even help with external validity (under assumptions)

Next week

- We will look at some **identification strategies** for observational studies:
    - Natural experiments and differences-in-differences.
- What **assumptions** need to hold?
- How do we **identify a natural experiment**?
- What does **DD** buy us?

References

- Angrist, J. and S. Pischke. (2015). "Mastering Metrics". *Chapter 2.*
- Heiss, A. (2020). "Program Evaluation for Public Policy". *Class 7: Randomization and Matching, Course at BYU*
- Imbens, G. and D. Rubin. (2015). "Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction". *Chapter 3*
- Cunningham, S. (2021). "Causal Inference: The Mixtape". *Chapter 5*