Studying Social Inequality with Data Science

INFO 3370 / 5371
Spring 2023

Causal inference: Connections to statistical modeling

Learning goals for today

By the end of class, you will be able to

- connect causal inference (a missing data problem)

  to statistical modeling (predicting missing data)

A running example

We should raise taxes on high earners to fund programs that seek to correct injustice

- 1 = Agree
- 0 = Disagree

A running example

We should raise taxes on high earners to fund programs that seek to correct injustice

- 1 = Agree
- 0 = Disagree

What is the average causal effect of taking this class on preferences for taxation to reduce injustice?

- why might it be big?
- why might it be small?
- why is it hard to know the answer?

Using potential outcomes

Each Row is a Student in This Class	Outcome under 3370	Outcome under no 3370
	$Y_1^{\text{Takes 3370}}$	$Y_1^{\text{No 3370}}$
	$Y_2^{\text{Takes 3370}}$	$Y_2^{\text{No 3370}}$
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Y = We should raise taxes on high earners to fund programs that seek to correct injustice

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Y = We should raise taxes on high earners to fund programs that seek to correct injustice

How could we learn about the (?)

Strategy 1: People who nearly took the class

Strategy 1: People who nearly took the class

- Some of the class was on the waitlist
  - some got in
  - others didn't

Strategy 1: People who nearly took the class

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?	$Y_7^{\text{No 3370}}$
?	$Y_8^{\text{No 3370}}$

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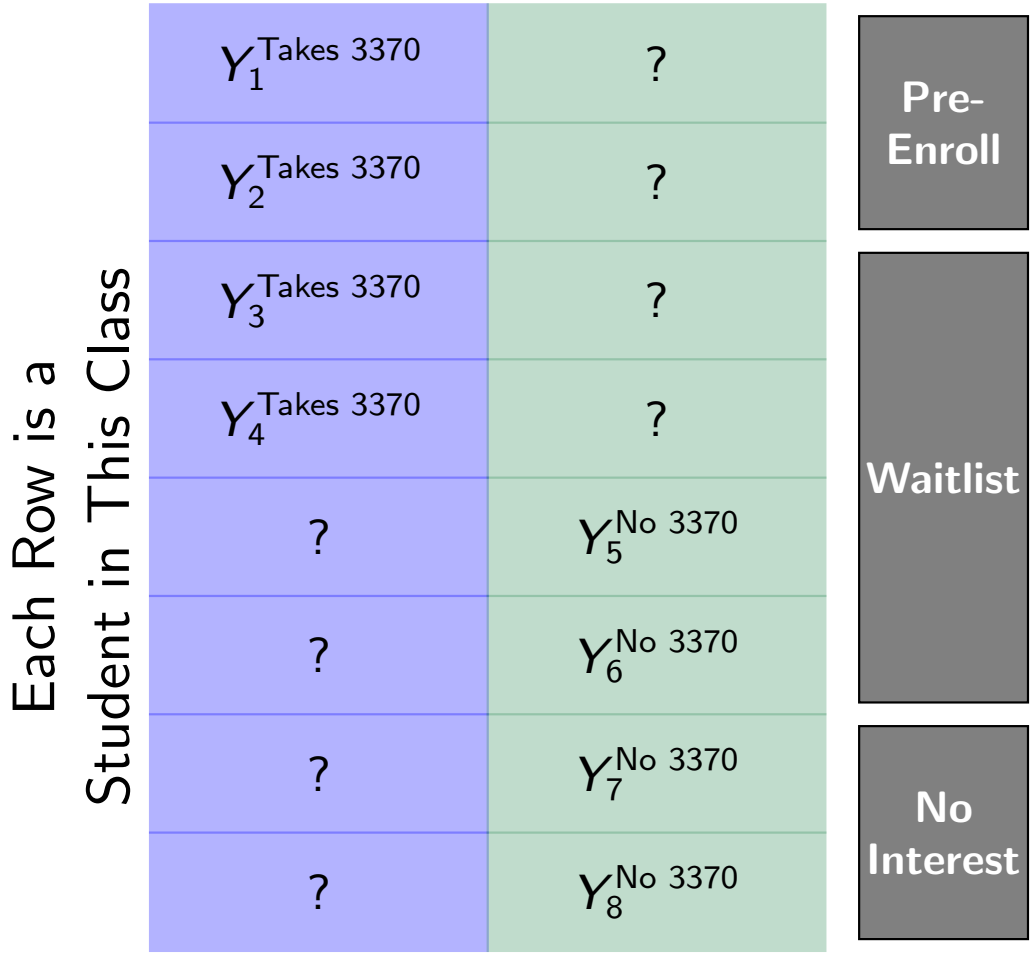

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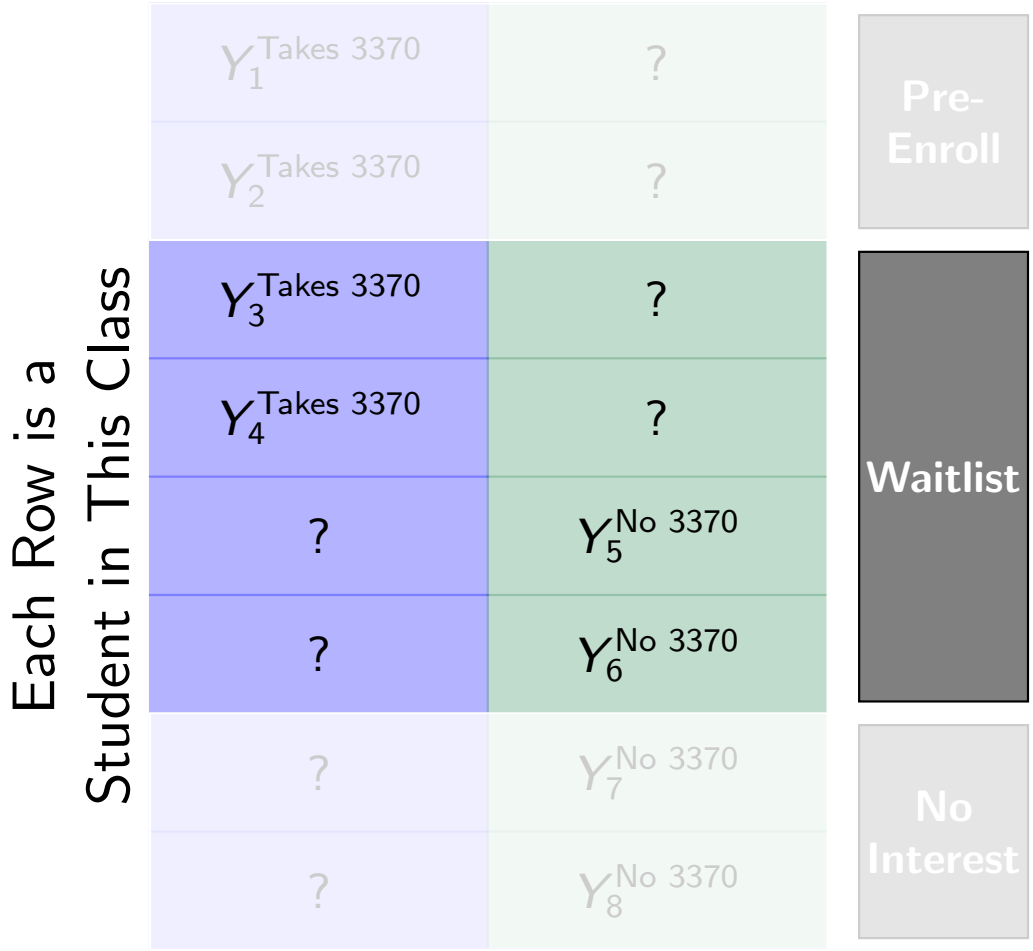

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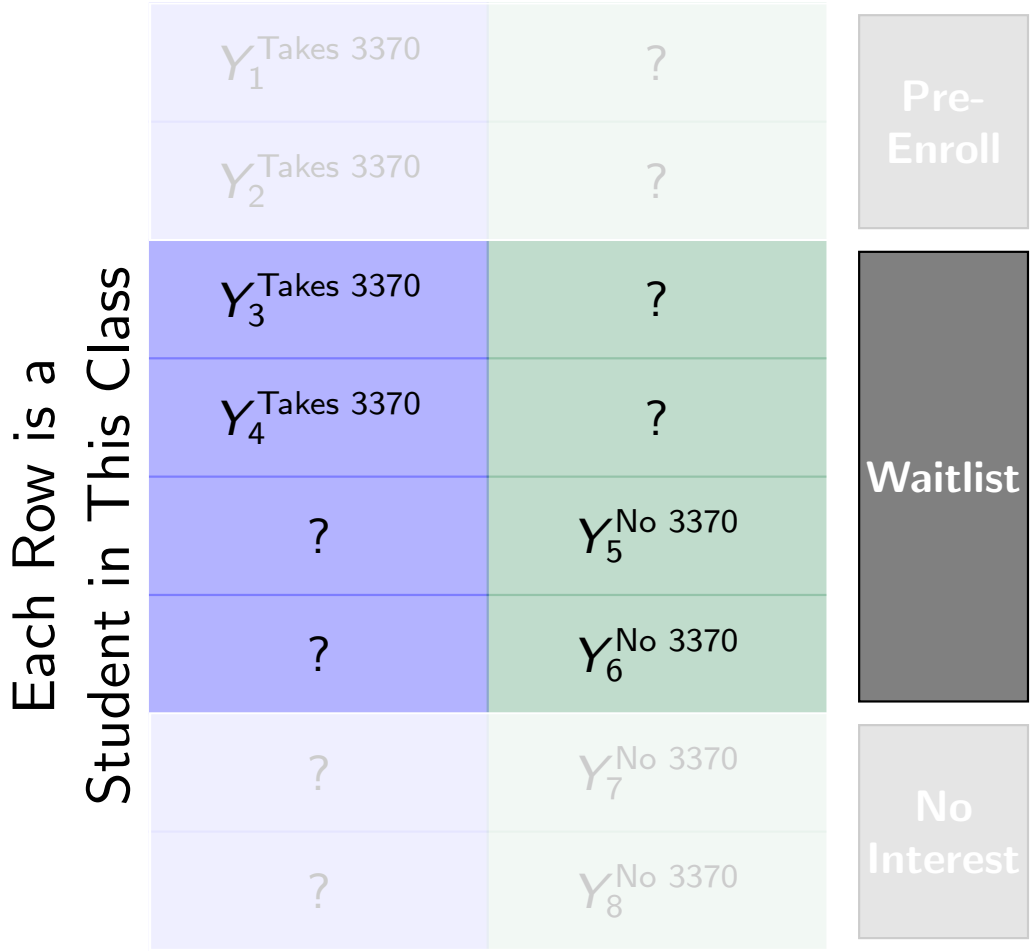

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Benefits of strategy

Drawbacks

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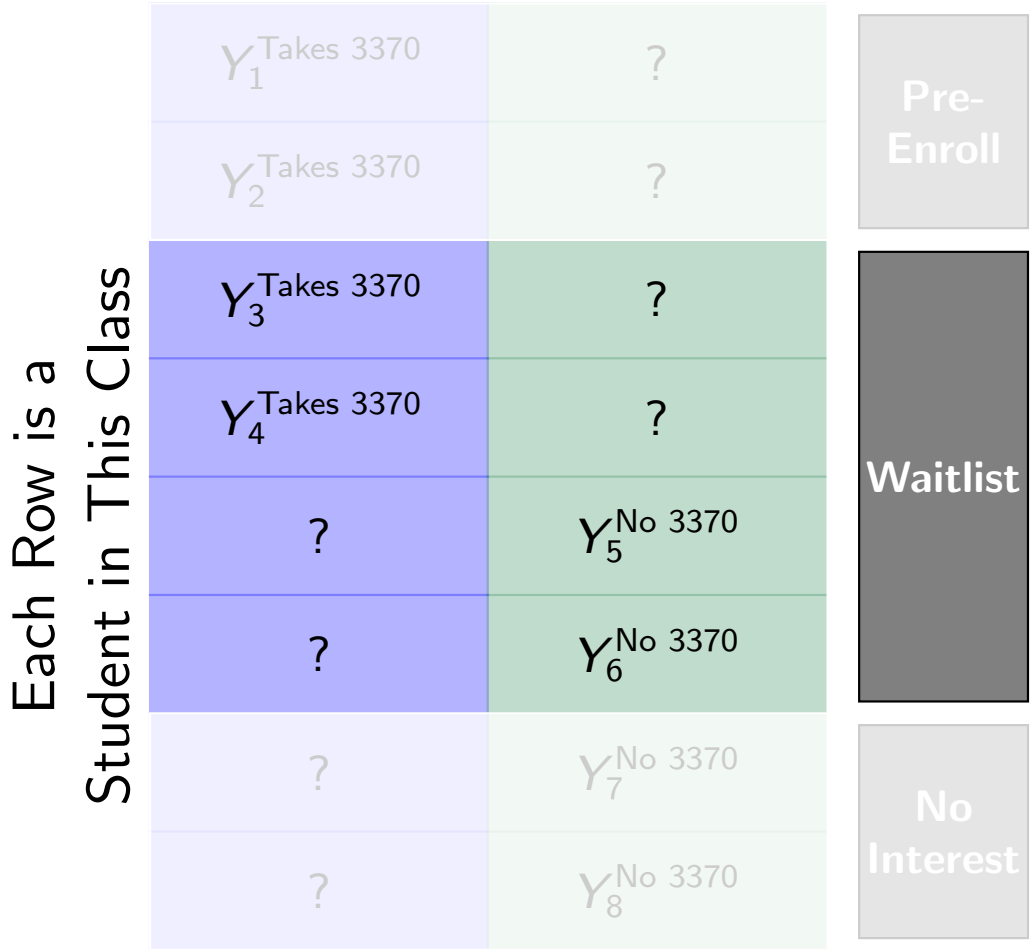

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Benefits of strategy

Credible

Drawbacks

Limited target population

Strategy 1: People who nearly took the class

Generalizing: Causal strategies in this domain

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- instrumental variables

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These strategies identify causal effects
by focusing on a feasible subpopulation
where treatment assignment is well-understood

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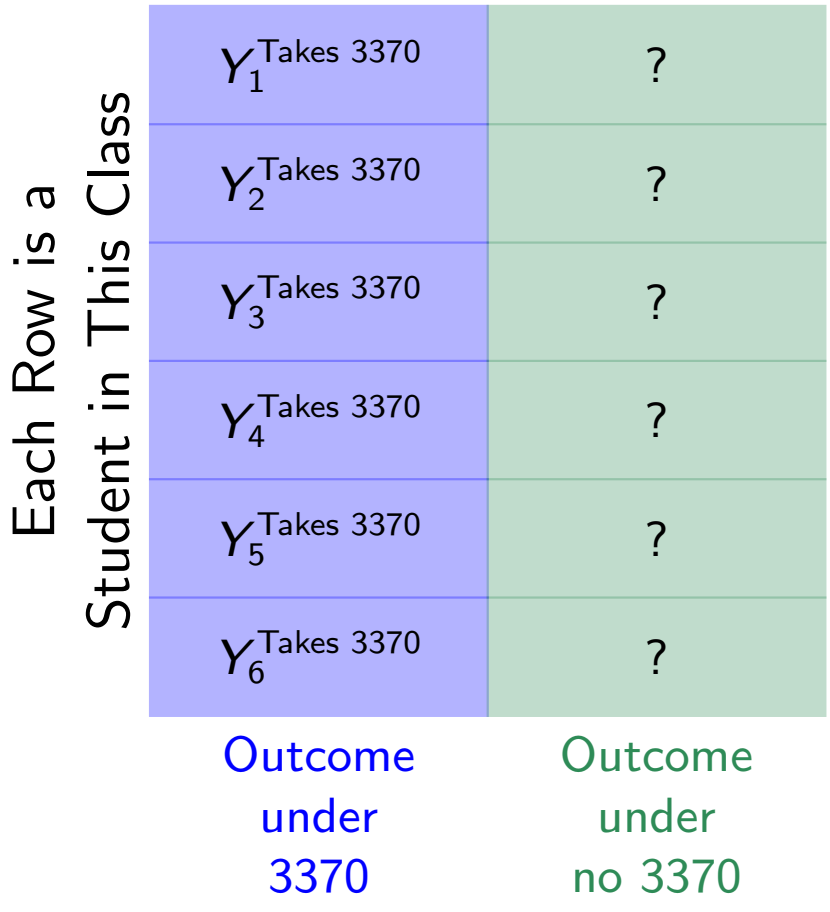

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Strategy 2: Find your look-alikes on relevant dimensions

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For each of you, we could compare

1. your opinion after 3370
2. the average opinion of non-3370 students who look like you

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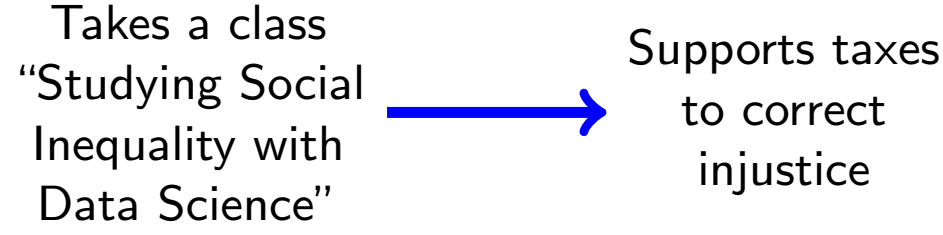
On what dimensions should they look like you?

Strategy 2: Find your look-alikes on relevant dimensions

Causal diagrams can help us reason about the adjustment set

- nodes are random variables
- edges are causal relationships



To learn more about causal graphs, see Pearl & Mackenzie 2018

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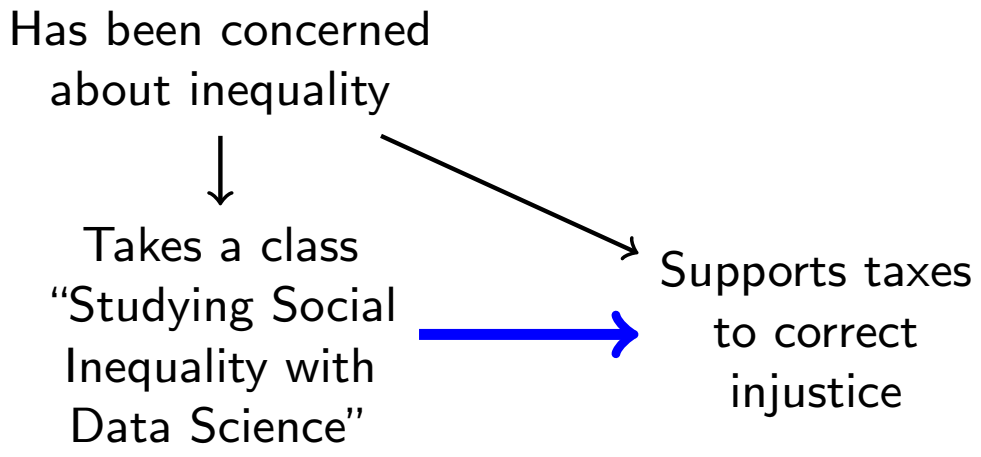

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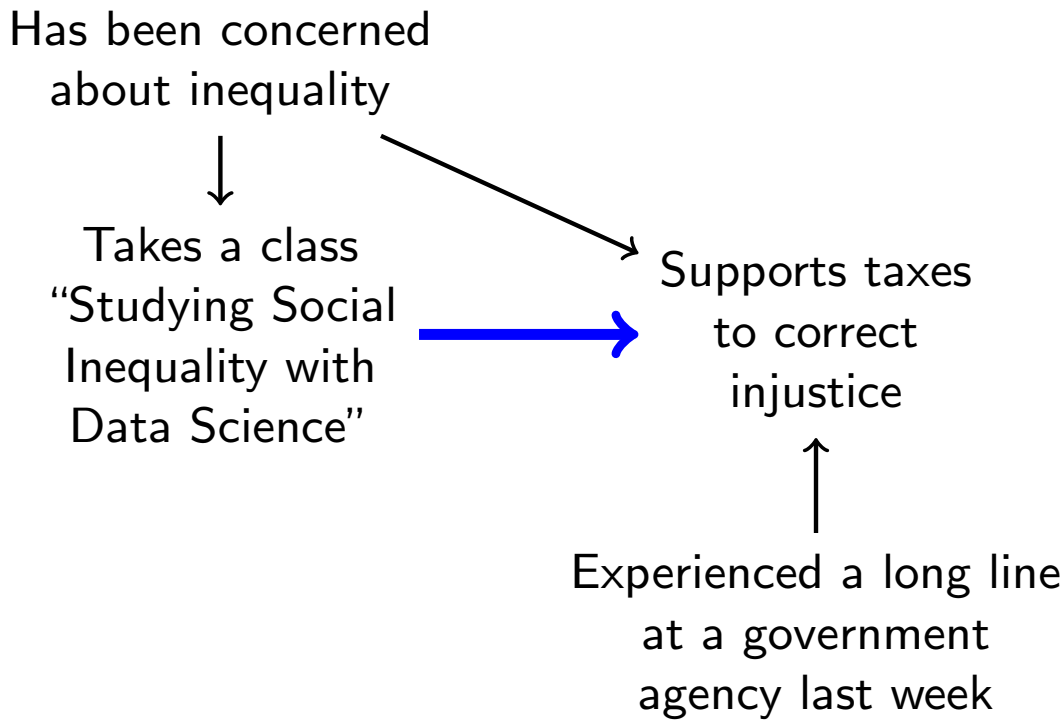

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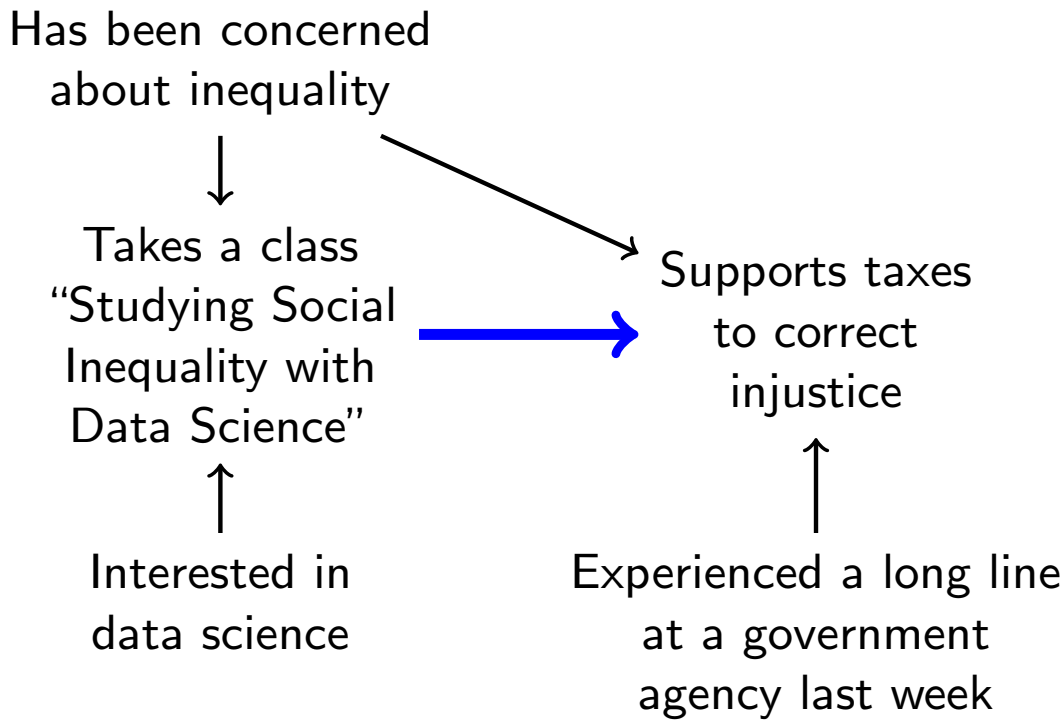

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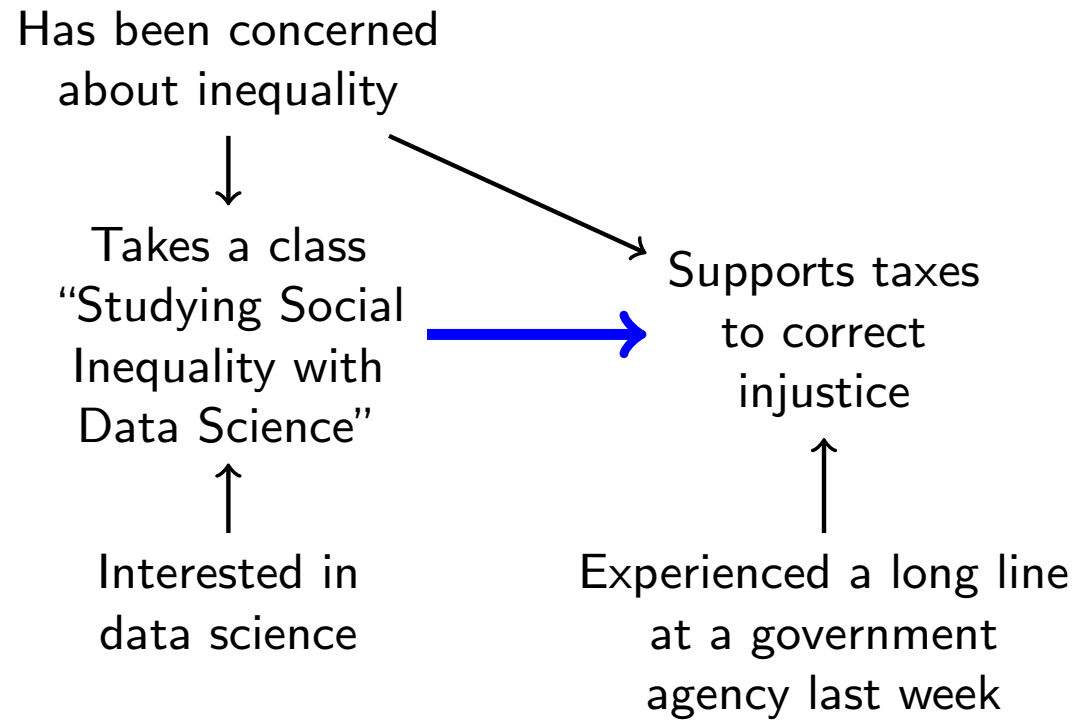

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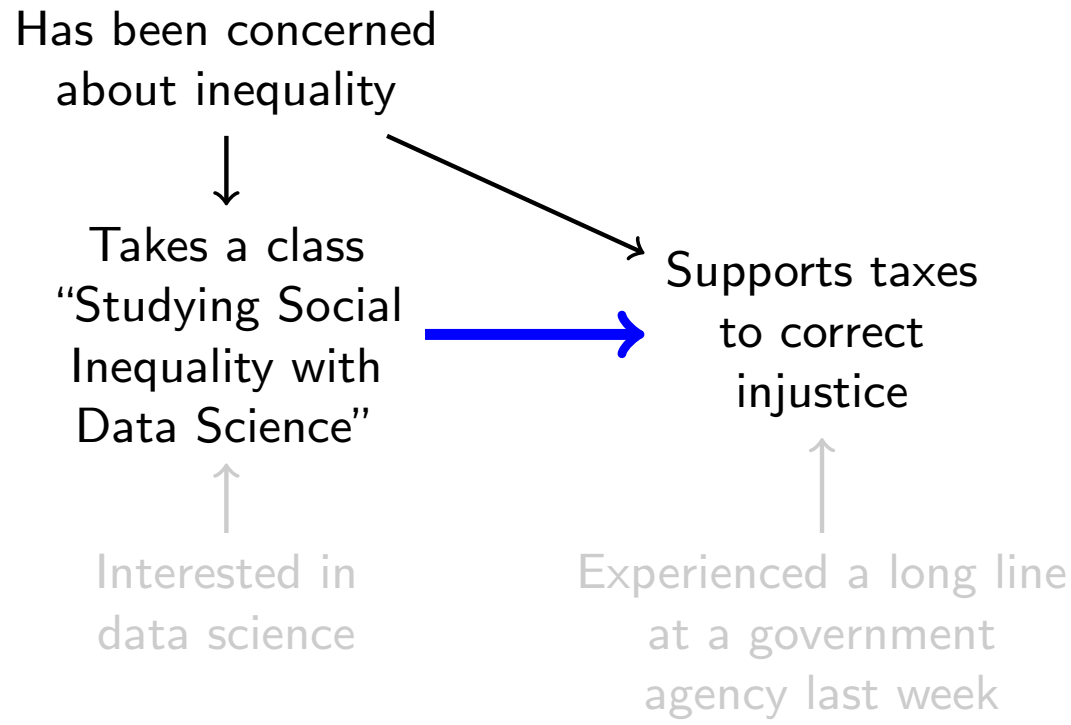

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Strategy 2: Find your look-alikes on relevant dimensions

Benefits

- Full target population

Drawbacks

- May be less credible than approaches like the waitlist

Strategy 2: Generalizing to a model

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Causal assumption: On average,

$$Y_{\text{You}}^{\text{No 3370}} \approx \text{E}(Y_{\text{Others}}^{\text{No 3370}} \mid \text{Look like you})$$

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The right side can be modeled statistically

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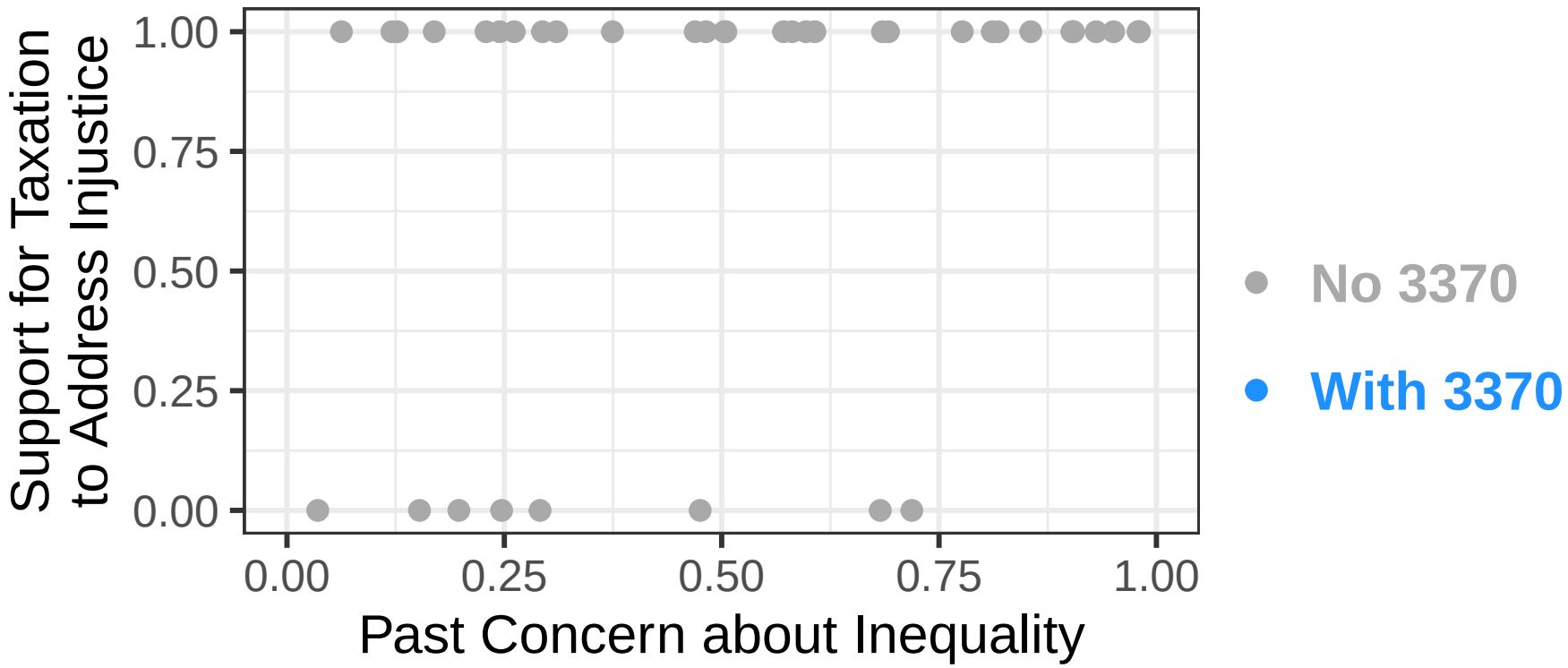
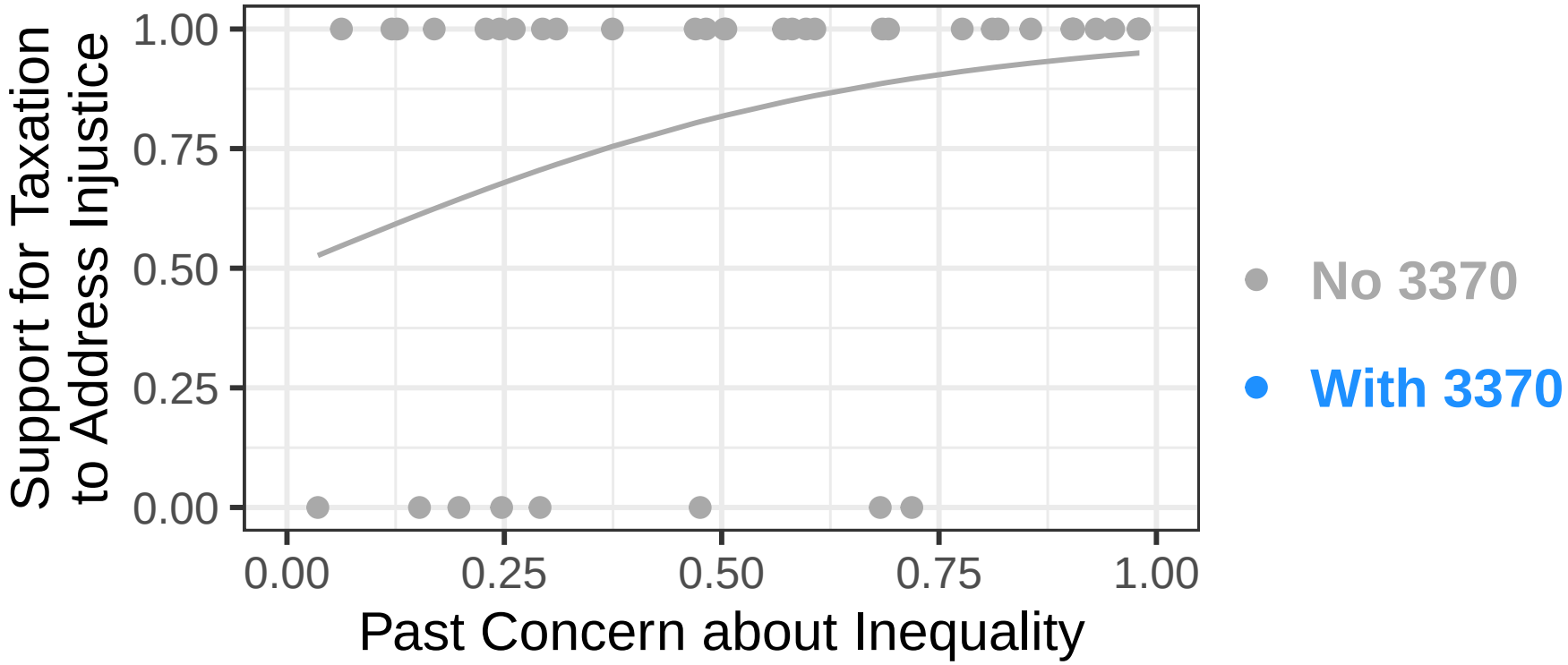


1) Find control units who didn't take this class

Strategy 2: Generalizing to a model



2) Model their outcomes given pre-treatment variables

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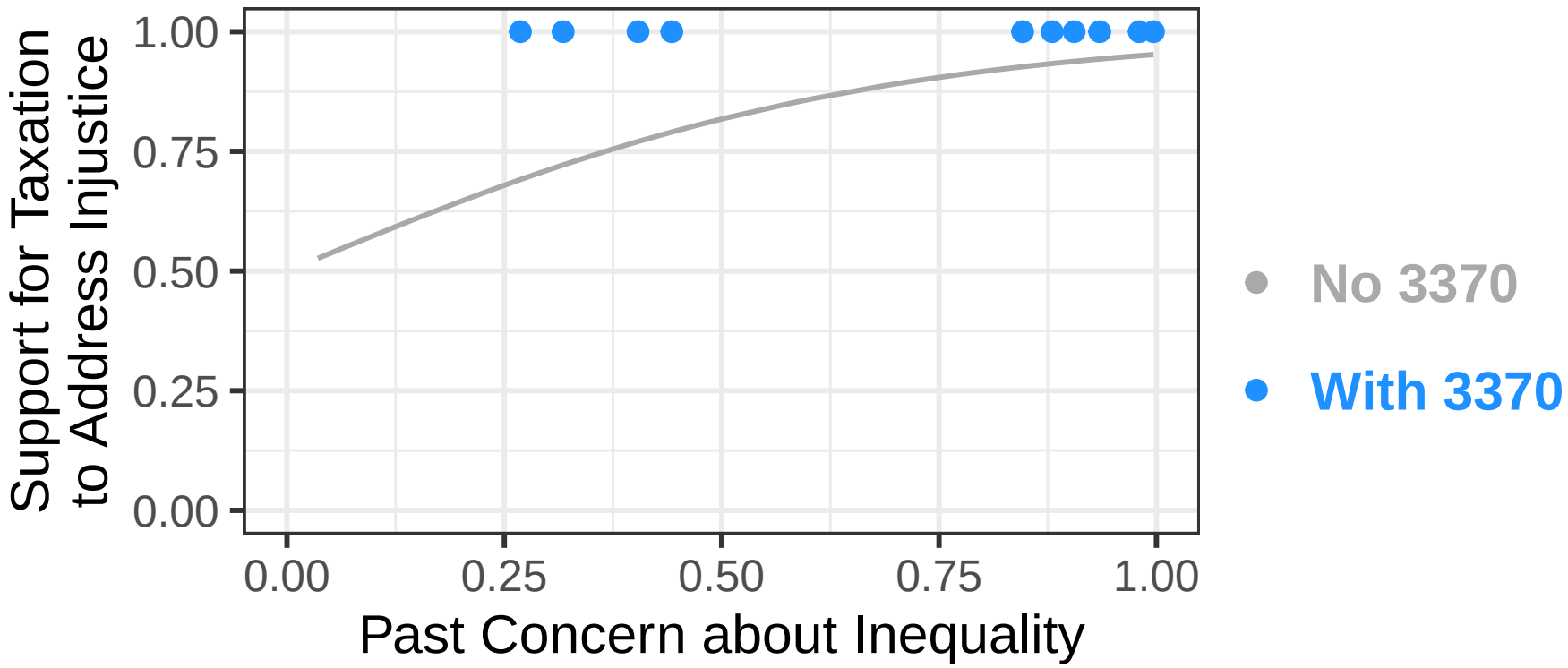

3) Find the treated units of interest

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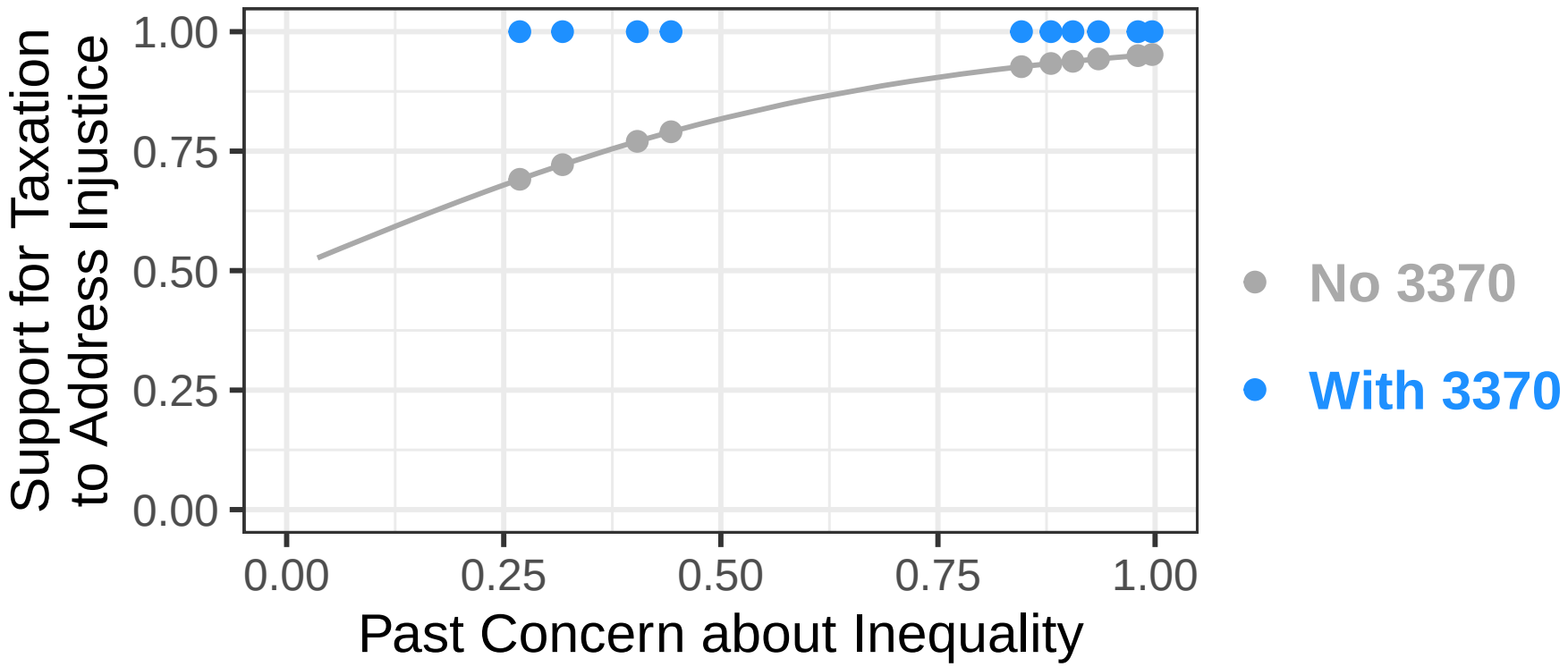

4) Predict their counterfactual outcomes

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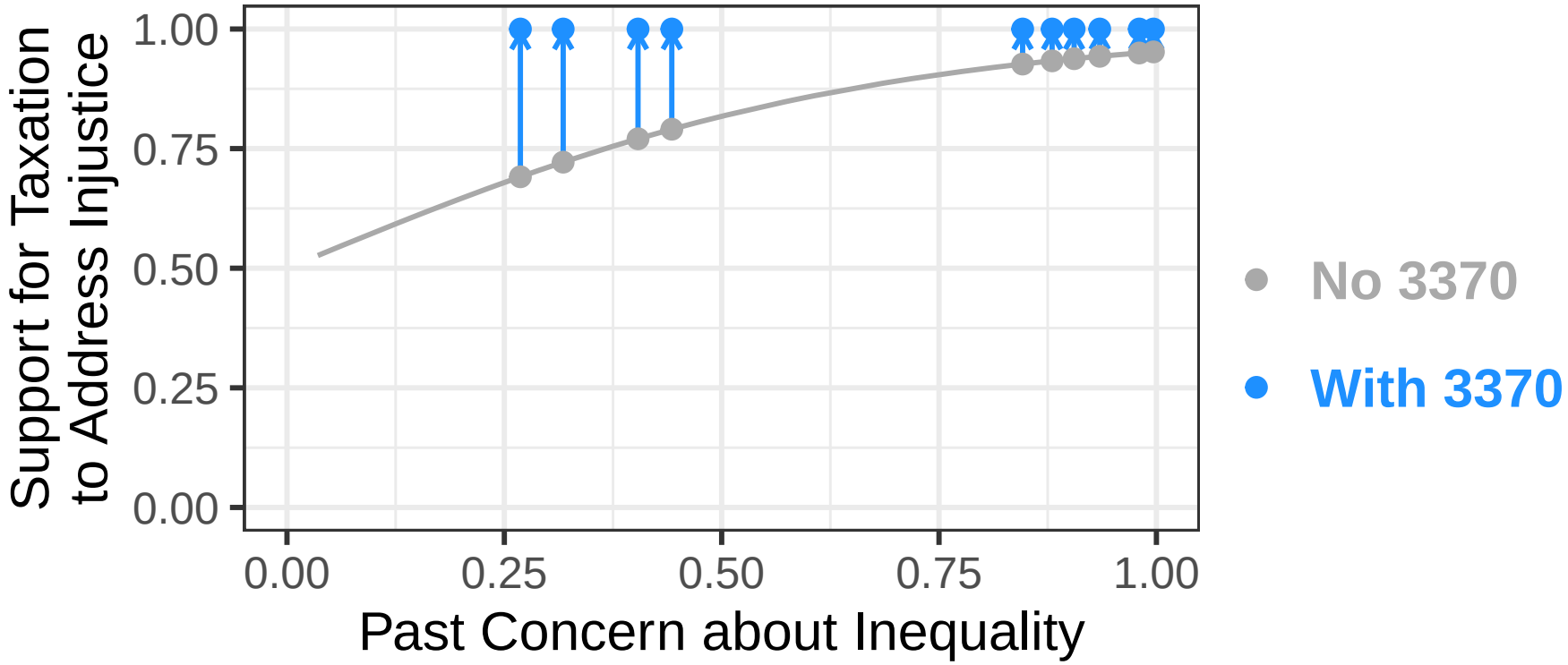

5) Infer causal effect for each person. Average over people

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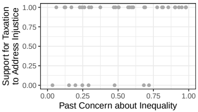

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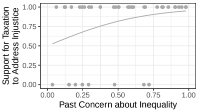

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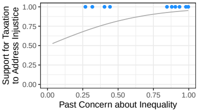

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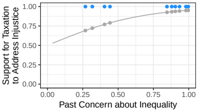

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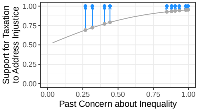

Summary: Causal inference is a missing data problem

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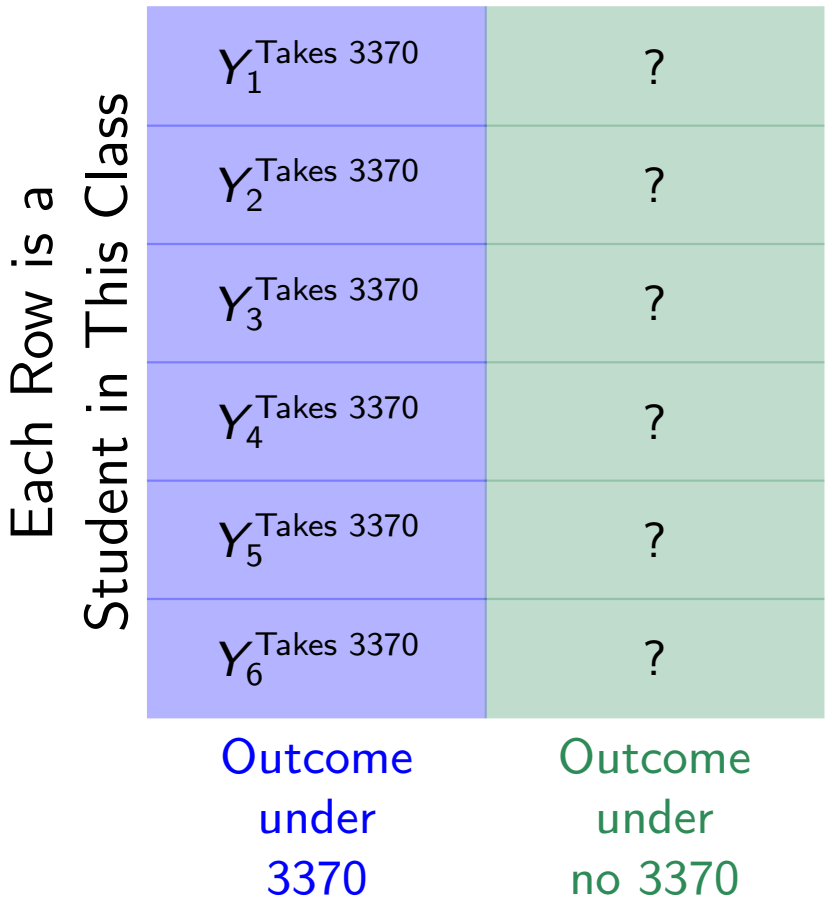

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General approach

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General approach

1) Define potential outcomes

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General approach

1) Define potential outcomes
2) Define target population

Summary: Causal inference is a missing data problem

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General approach

1) Define potential outcomes
2) Define target population
3) Make causal assumptions

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General approach

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3) Make causal assumptions
4) Model unobserved outcomes

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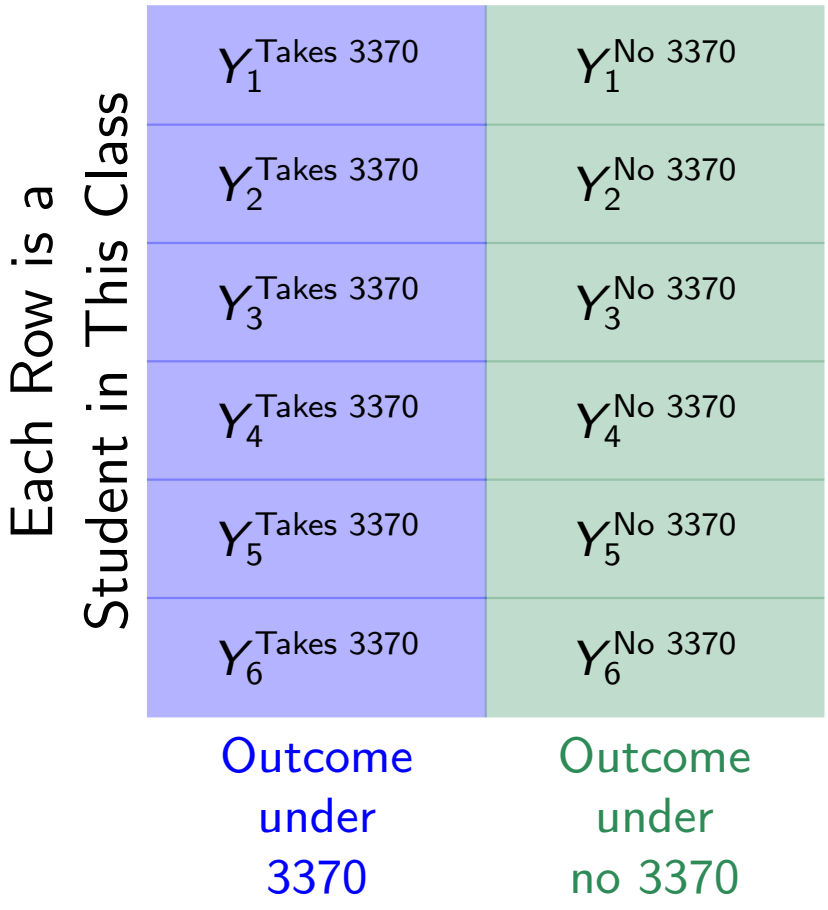

General approach

1) Define potential outcomes
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3) Make causal assumptions
4) Model unobserved outcomes
5) Predict them

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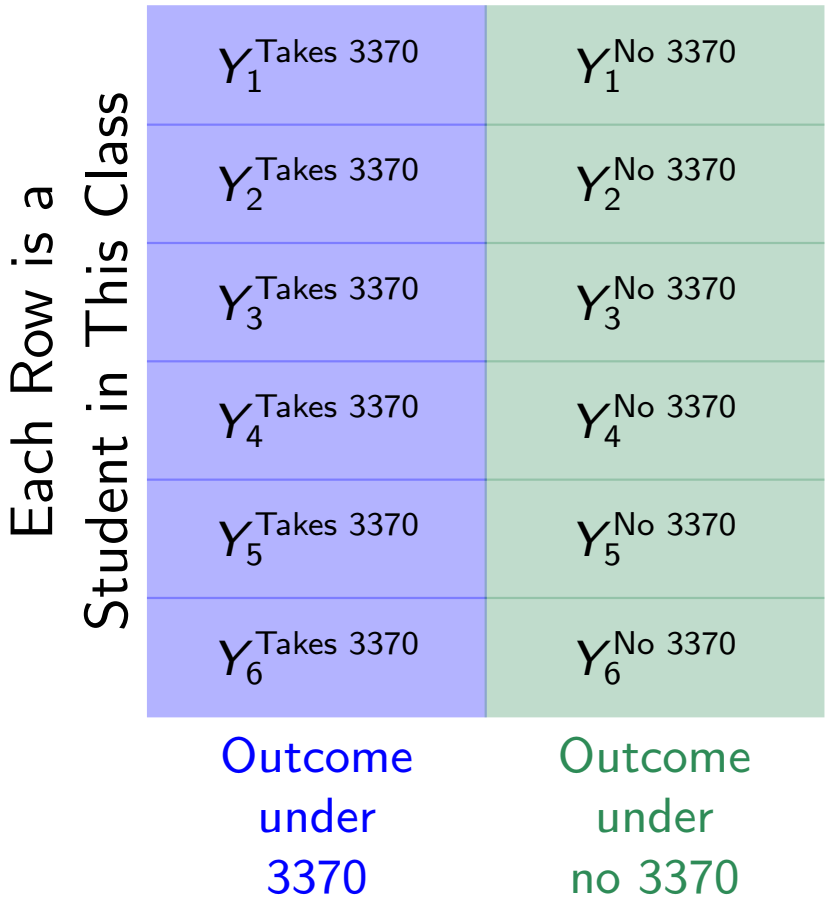

General approach

1) Define potential outcomes
2) Define target population
3) Make causal assumptions
4) Model unobserved outcomes
5) Predict them
6) Report an average

In what settings

- is it important to ask a causal question about inequality?
- is it sufficient to ask a descriptive question?

Learning goals for today

By the end of class, you will be able to

- connect causal inference (a missing data problem)

  to statistical modeling (predicting missing data)