# The **gap-closing estimand**

## A causal approach to study **interventions** that **close disparities** across social categories

Slides at
ianlundberg.org

Software at
ilundberg.github.io/gapclosing

**Ian Lundberg**

UCLA Sociology and
California Center for Population Research
ianlundberg@ucla.edu

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Paper in *Sociological Methods and Research*. Replication code on Dataverse. R package `gapclosing` on CRAN.
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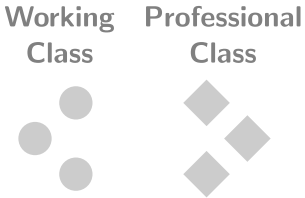


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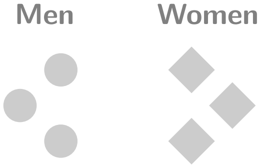


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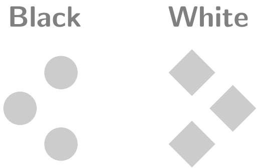


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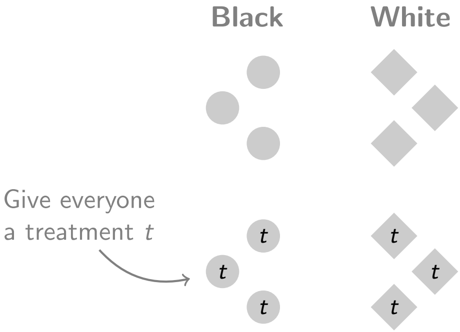


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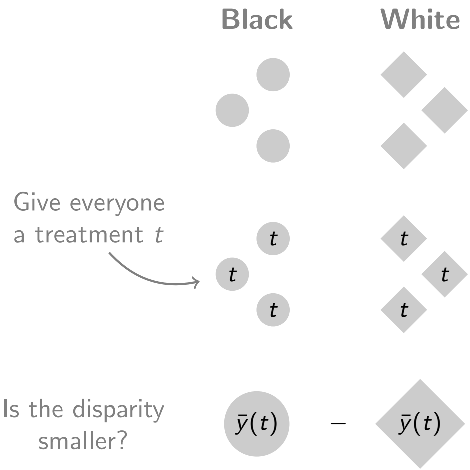


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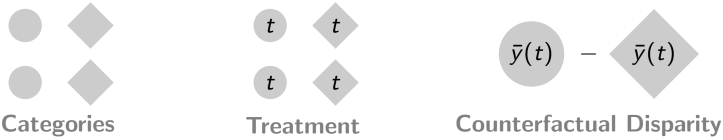
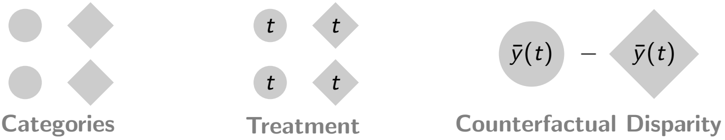
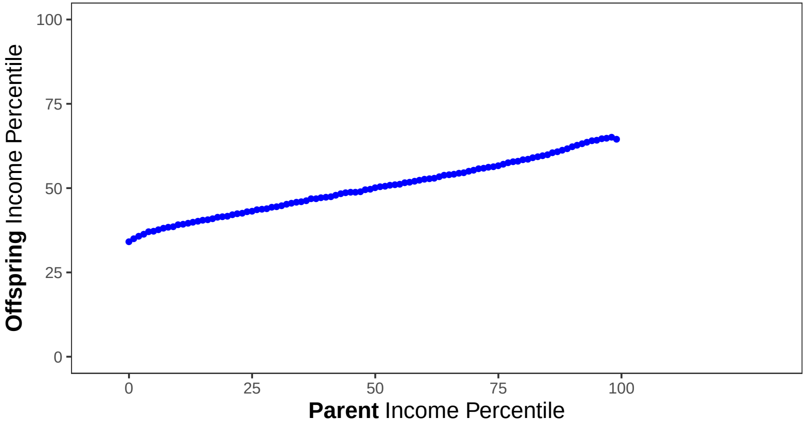
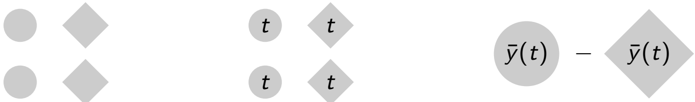

t t
t t
Categories
Treatment
$\bar{y}(t)$ − $\bar{y}(t)$
Counterfactual Disparity

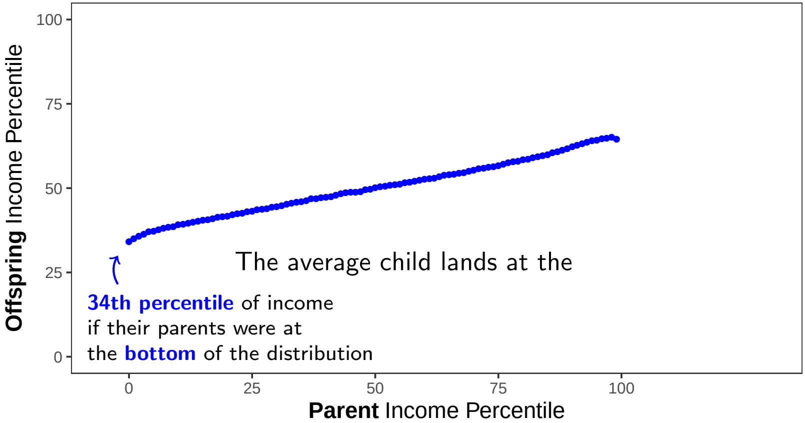



Chetty et al. 2017




Categories Treatment Counterfactual Disparity

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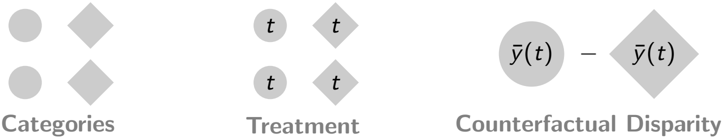


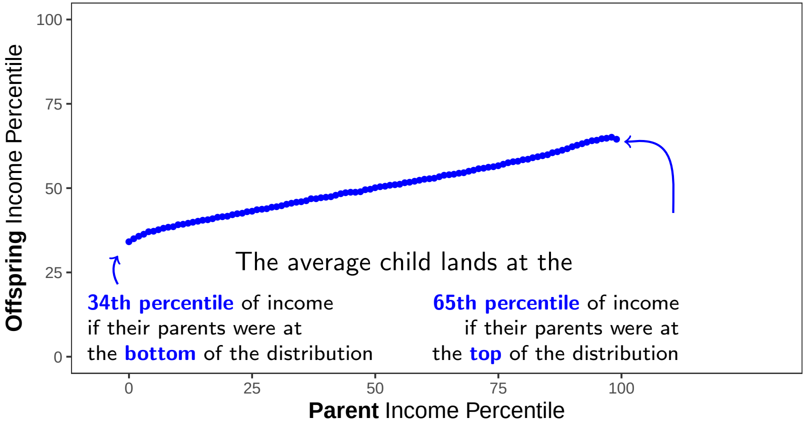


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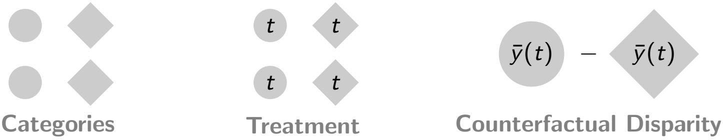


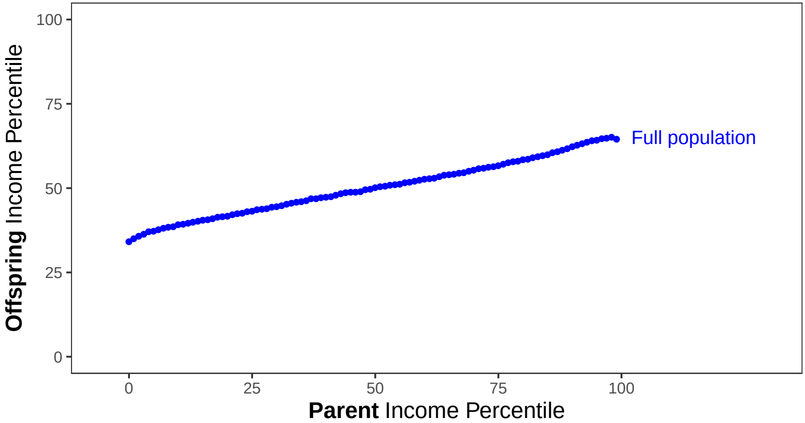


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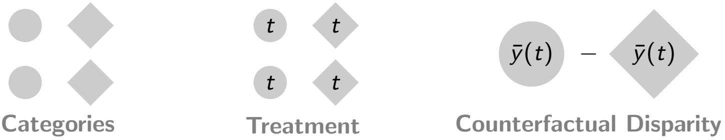


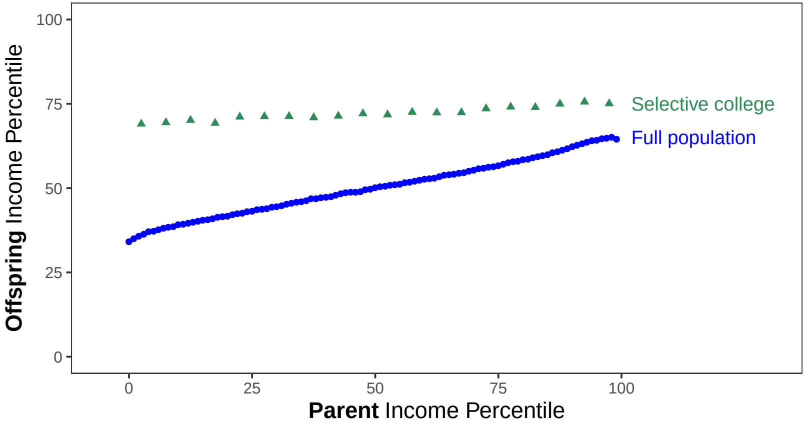


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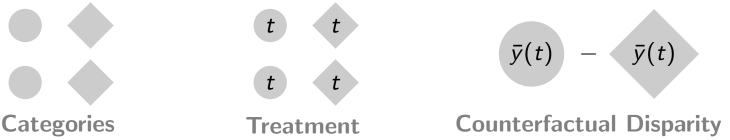


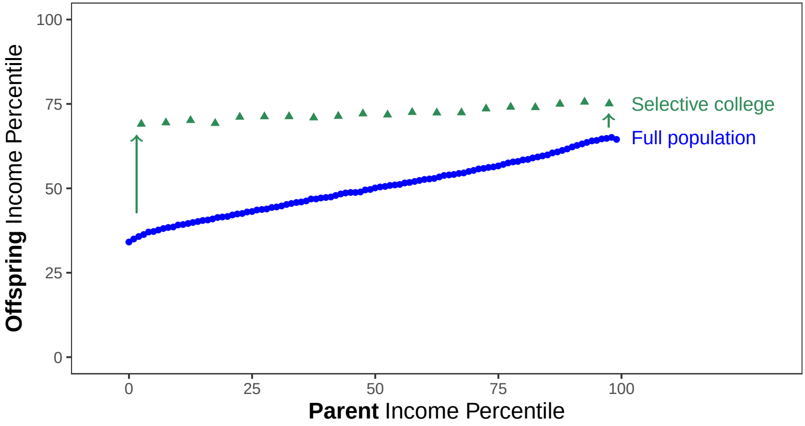


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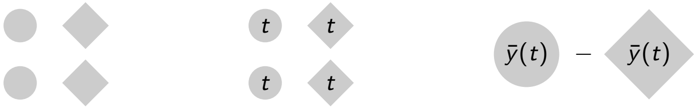
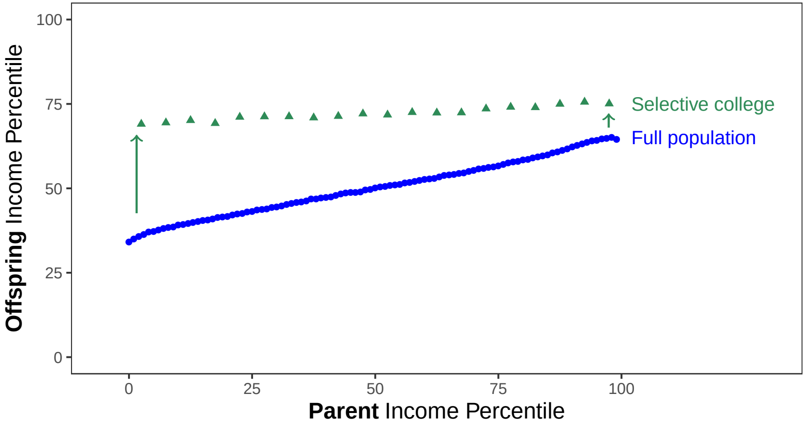



**Categories** Parent Income

**Treatment** Selective College

**Counterfactual Disparity** Offspring Income




**Chetty et al. 2017**

# The Gap-Closing Estimand

A causal approach to study interventions that close disparities across social categories

- Past work: Causal decomposition analysis
- Define the estimand
    - what is the treatment?
    - what is the scope of the intervention?
- Identify the estimand
    - choose a sufficient adjustment set
- Estimate
    - by outcome modeling
    - by weighting
    - by doubly robust estimation
- Produce software
- Impact: Others using these ideas

# The Gap-Closing Estimand

A causal approach to study interventions that close disparities across social categories

- Past work: Causal decomposition analysis
- Define the estimand
  - what is the treatment?
  - what is the scope of the intervention? (contribution)
- Identify the estimand
  - choose a sufficient adjustment set
- Estimate
  - by outcome modeling
  - by weighting
  - by doubly robust estimation (contribution)
- Produce software (contribution)
- Impact: Others using these ideas

# Past work: Causal decomposition analysis

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Unadjusted

$$Y = \beta(\texttt{Black}) + \epsilon$$

Adjusted

$$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$$

# Past work: Causal decomposition analysis

| Unadjusted | Adjusted |
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Effect of race

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× Effect of race

Vanderweele & Robinson 2014

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Choice of intervention targets

Jackson & Vanderweele 2018

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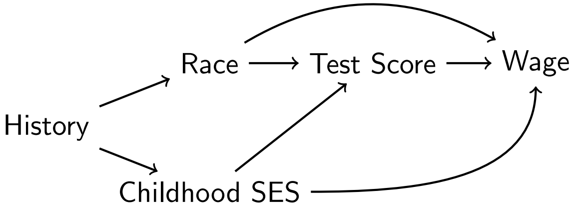

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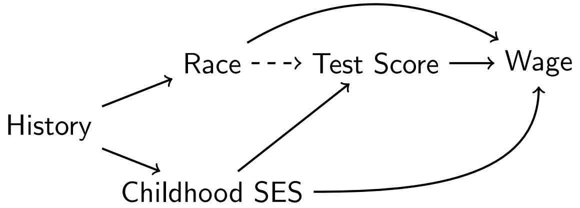

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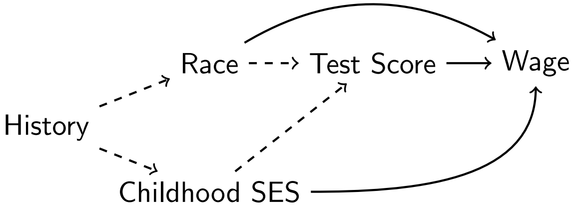

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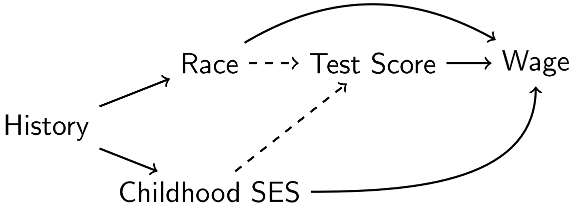

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Vanderweele & Robinson 2014

Choice of intervention targets

Jackson & Vanderweele 2018

Equity: What should we equalize?

Jackson 2021

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Choice of intervention targets

Jackson & Vanderweele 2018

Equity: What should we equalize?

Jackson 2021

Systems may adapt to maintain inequity

Jackson & Arah 2020

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# Define an intervention

Using the Chetty et al. 2017 example,

What gap in respondent incomes would remain
across categories of parent income
if we intervened to send people to selective colleges?

Interpret with respect to a **target trial** (Hernán & Robins 2016)

# Interpret with respect to a **target trial** (Hernán & Robins 2016)

1. Sample $\mathcal{S}$ from the population

## Interpret with respect to a **target trial** (Hernán & Robins 2016)

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3. Observe the disparity across categories $X$

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Goal: Expected result over hypothetical samples $\mathcal{S}$

Interpret with respect to a **target trial** (Hernán & Robins 2016)

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1. Take the entire population $\mathcal{P}$

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Goal: Result of this procedure

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Difficulty: Causal inference
Equilibrium dynamics

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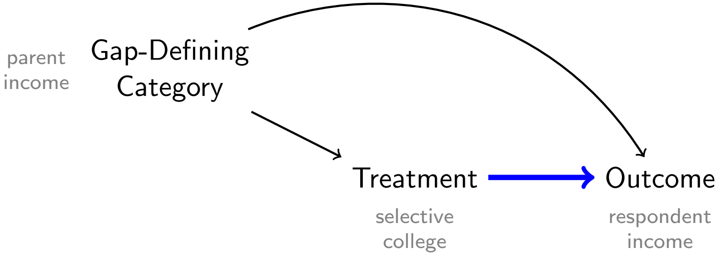
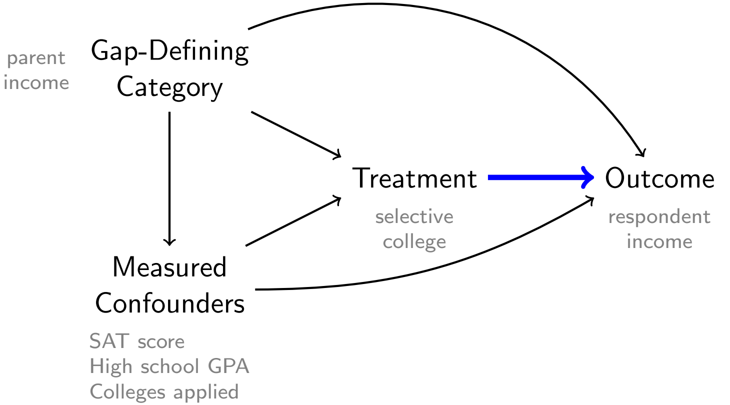

parent income
Gap-Defining Category
Treatment
Outcome
selective college
respondent income

Pearl 2009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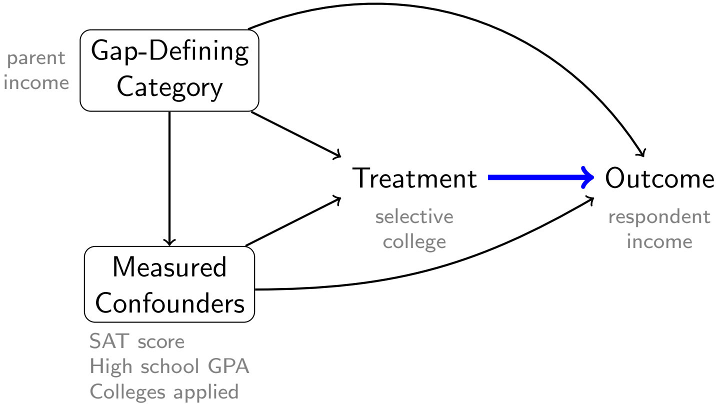
Measured
Confounders
SAT score
High school GPA
Colleges applied

Pearl 2009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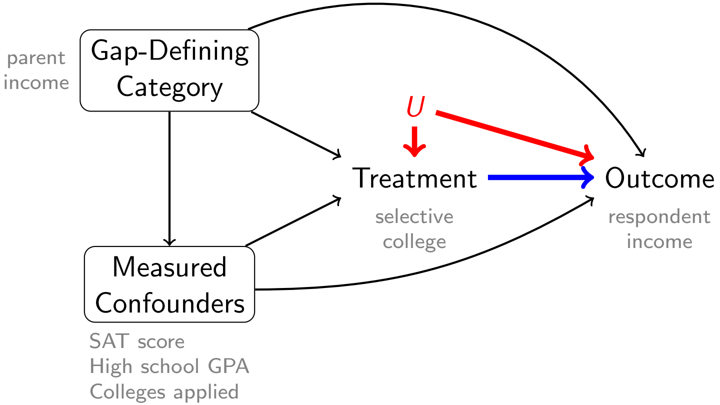
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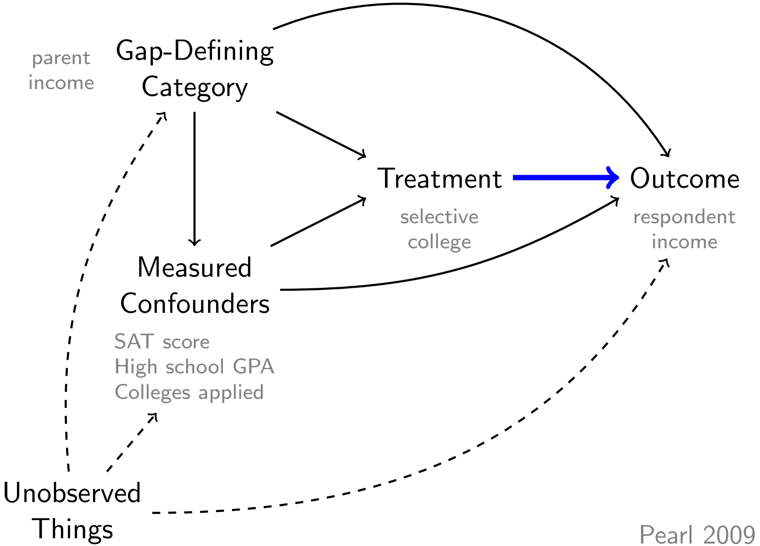
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Unobserved
Things
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# The Gap-Closing Estimand

A causal approach to study interventions that close disparities across social categories

- Past work: Causal decomposition analysis
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  - by outcome modeling
  - by weighting
  - by doubly robust estimation
- Produce software
- Impact: Others using these ideas

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
| | Person 2 | $Y_2$ | ? |
| | Person 3 | $Y_3$ | ? |
| **People in category 2** | Person 4 | ? | $Y_4$ |
| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
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# Learn a prediction function

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| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

## Predict the whole table

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | $\hat{Y}_1(0)$ |
| | Person 2 | $\hat{Y}_2(1)$ | $\hat{Y}_2(0)$ |
| | Person 3 | $\hat{Y}_3(1)$ | $\hat{Y}_3(0)$ |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | $\hat{Y}_4(0)$ |
| | Person 5 | $\hat{Y}_5(1)$ | $\hat{Y}_5(0)$ |
| | Person 6 | $\hat{Y}_6(1)$ | $\hat{Y}_6(0)$ |

Robins 1986
Hahn 1998

## Learn a prediction function

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|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
| | Person 2 | $Y_2$ | ? |
| | Person 3 | $Y_3$ | ? |
| **People in category 2** | Person 4 | ? | $Y_4$ |
| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

## Predict the whole table

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | $\hat{Y}_1(0)$ |
| | Person 2 | $\hat{Y}_2(1)$ | $\hat{Y}_2(0)$ |
| | Person 3 | $\hat{Y}_3(1)$ | $\hat{Y}_3(0)$ |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | $\hat{Y}_4(0)$ |
| | Person 5 | $\hat{Y}_5(1)$ | $\hat{Y}_5(0)$ |
| | Person 6 | $\hat{Y}_6(1)$ | $\hat{Y}_6(0)$ |

Robins 1986
Hahn 1998

## Learn a prediction function

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
| | Person 2 | $Y_2$ | ? |
| | Person 3 | $Y_3$ | ? |
| **People in category 2** | Person 4 | ? | $Y_4$ |
| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

## Predict the whole table

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | $\hat{Y}_1(0)$ |
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| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | $\hat{Y}_4(0)$ |
| | Person 5 | $\hat{Y}_5(1)$ | $\hat{Y}_5(0)$ |
| | Person 6 | $\hat{Y}_6(1)$ | $\hat{Y}_6(0)$ |

## Problem: Optimization for the wrong task

## Learn a prediction function

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
| | Person 2 | $Y_2$ | ? |
| | Person 3 | $Y_3$ | ? |
| **People in category 2** | Person 4 | ? | $Y_4$ |
| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

## Predict the whole table

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | $\hat{Y}_1(0)$ |
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## Problem: Optimization for the wrong task

Prediction error over
**observed**
cases

## Learn a prediction function

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | ? | $Y_1$ |
| | Person 2 | $Y_2$ | ? |
| | Person 3 | $Y_3$ | ? |
| **People in category 2** | Person 4 | ? | $Y_4$ |
| | Person 5 | $Y_5$ | ? |
| | Person 6 | ? | $Y_6$ |

## Predict the whole table

| | | Outcome under treatment | Outcome under control |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | $\hat{Y}_1(0)$ |
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## Problem: Optimization for the wrong task

Prediction error over **observed** cases

vs

Prediction error over **all** cases

# Solution: Reweight errors to approximate the correct task

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| | | Prediction under treatment |
|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ |
| | Person 2 | $\hat{Y}_2(1)$ |
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# Solution: Reweight errors to approximate the correct task

| | | Prediction under treatment | Outcome under treatment |
|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | ? |
| | Person 2 | $\hat{Y}_2(1)$ | $Y_2$ |
| | Person 3 | $\hat{Y}_3(1)$ | $Y_3$ |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | ? |
| | Person 5 | $\hat{Y}_5(1)$ | $Y_5$ |
| | Person 6 | $\hat{Y}_6(1)$ | ? |

## Solution: Reweight errors to approximate the correct task

| | | Prediction under treatment | Outcome under treatment | Error |
|---|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | ? | ? |
| | Person 2 | $\hat{Y}_2(1)$ | $Y_2$ | $\hat{Y}_2(1) - Y_2$ |
| | Person 3 | $\hat{Y}_3(1)$ | $Y_3$ | $\hat{Y}_3(1) - Y_3$ |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | ? | ? |
| | Person 5 | $\hat{Y}_5(1)$ | $Y_5$ | $\hat{Y}_5(1) - Y_5$ |
| | Person 6 | $\hat{Y}_6(1)$ | ? | ? |

# Solution: Reweight errors to approximate the correct task

| | | Prediction under treatment | Outcome under treatment | Error | Weight on error |
|---|---|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | ? | ? | |
| | Person 2 | $\hat{Y}_2(1)$ | $Y_2$ | $\hat{Y}_2(1) - Y_2$ | 3 / 2 |
| | Person 3 | $\hat{Y}_3(1)$ | $Y_3$ | $\hat{Y}_3(1) - Y_3$ | 3 / 2 |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | ? | ? | |
| | Person 5 | $\hat{Y}_5(1)$ | $Y_5$ | $\hat{Y}_5(1) - Y_5$ | 3 |
| | Person 6 | $\hat{Y}_6(1)$ | ? | ? | |

# Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

| | | Prediction under treatment | Outcome under treatment | Error | Weight on error |
|---|---|---|---|---|---|
| **People in category 1** | Person 1 | $\hat{Y}_1(1)$ | ? | ? | |
| | Person 2 | $\hat{Y}_2(1)$ | $Y_2$ | $\hat{Y}_2(1) - Y_2$ | 3 / 2 |
| | Person 3 | $\hat{Y}_3(1)$ | $Y_3$ | $\hat{Y}_3(1) - Y_3$ | 3 / 2 |
| **People in category 2** | Person 4 | $\hat{Y}_4(1)$ | ? | ? | |
| | Person 5 | $\hat{Y}_5(1)$ | $Y_5$ | $\hat{Y}_5(1) - Y_5$ | 3 |
| | Person 6 | $\hat{Y}_6(1)$ | ? | ? | |

## Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

New Estimate: (Original Estimate) $-$ (Estimated Bias)

## Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

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Doubly Robust Estimation

Robins, Rotnitzky, & Zhao 1994
Bang & Robins 2005

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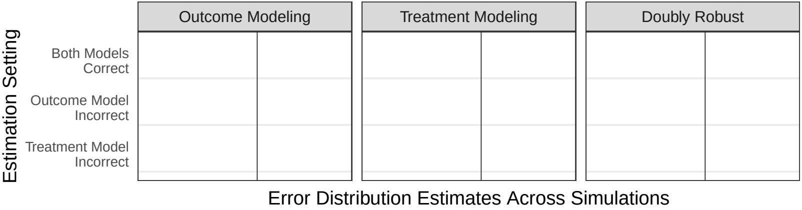


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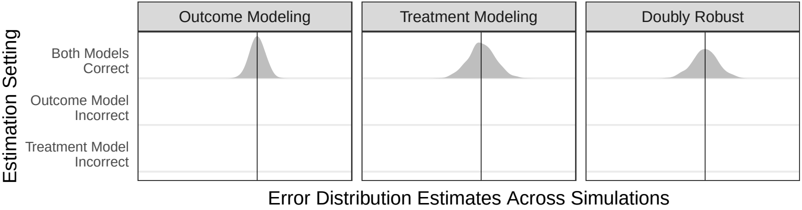


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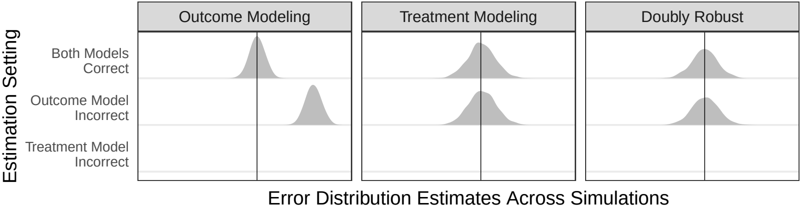


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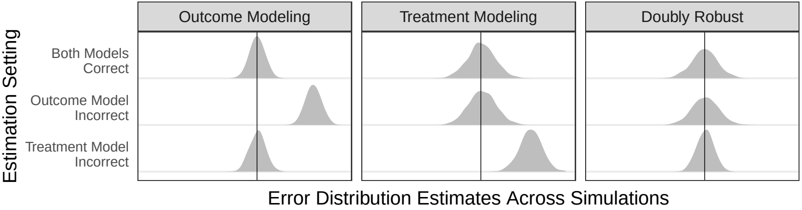


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Even better:

Chernozhukov et al. 2018
Bickel 1982

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Even better:

— Learn $\hat{Y}_i$ in sample A

— Estimate bias in sample B

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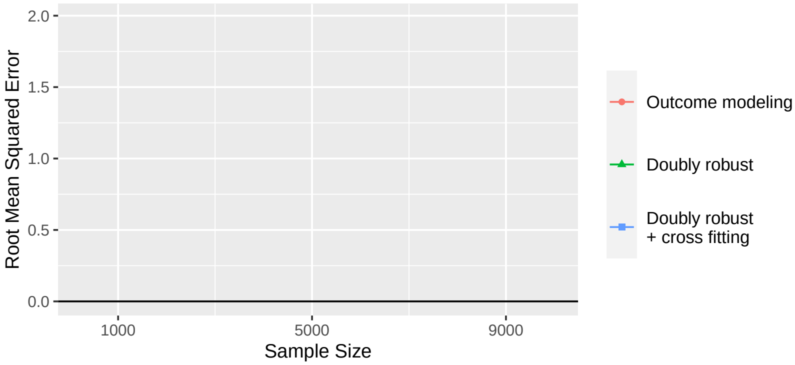

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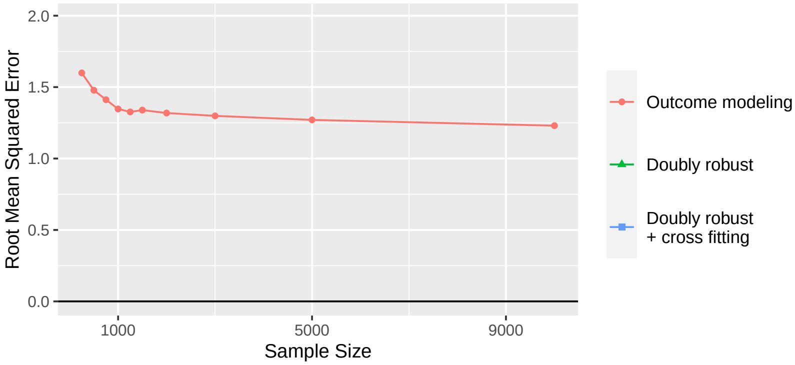

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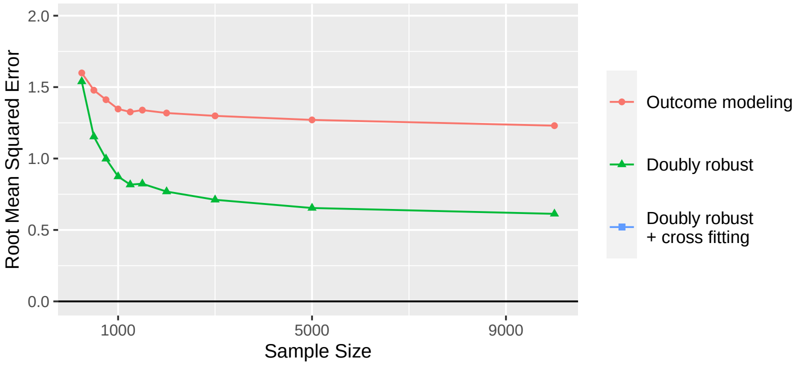

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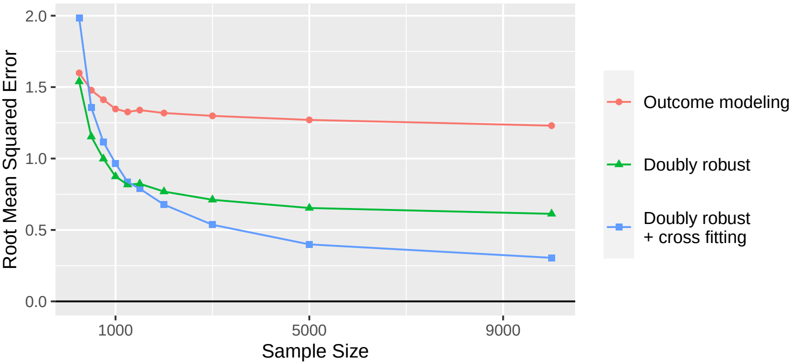

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Double Machine Learning

Chernozhukov et al. 2018
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Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

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Even better: — Double Machine Learning

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So complicated!

# The Gap-Closing Estimand

A causal approach to study interventions that close disparities across social categories

- Past work: Causal decomposition analysis
- Define the estimand
  - what is the treatment?
  - what is the scope of the intervention?
- Identify the estimand
  - choose a sufficient adjustment set
- Estimate
  - by outcome modeling
  - by weighting
  - by doubly robust estimation
- **Produce software**
- Impact: Others using these ideas

# gapclosing

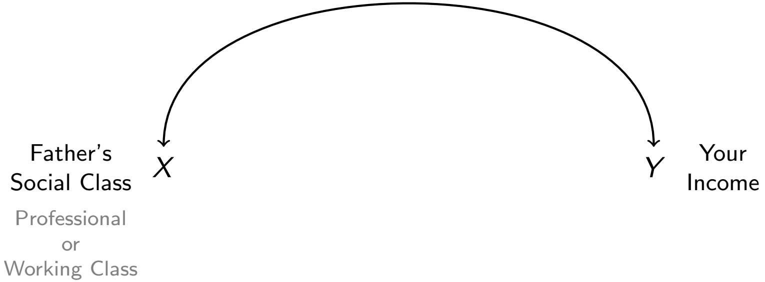
An R package to estimate gap closing estimands. Install this package with the command `devtools::install_github("ilundberg/gapclosing")`.

```
estimate <- gapclosing(
  data = simulated_data,
  outcome_formula = formula(outcome ~ category + confounder),
  treatment_formula = formula(treatment ~ category + confounder),
  category_name = "category",
  counterfactual_assignments = 1,
  outcome_algorithm = "ranger",
  treatment_algorithm = "ranger",
  sample_split = "cross_fit",
  se = T
)
```

```
       description estimate   se ci.min ci.max
       Factual gap     2.14 0.40   1.36    2.9
 Counterfactual gap     0.67 0.44  -0.19    1.5
```

# Empirical Examples

# **Empirical Example 1**: Economic Mobility



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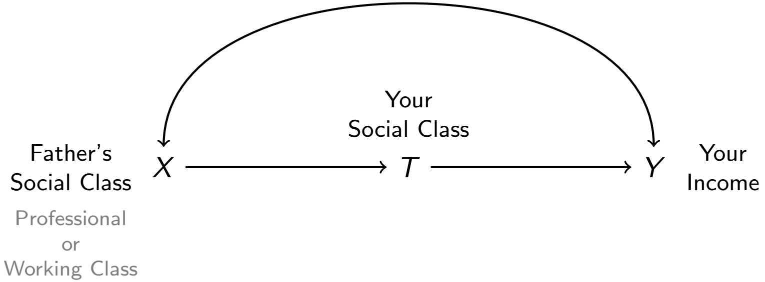

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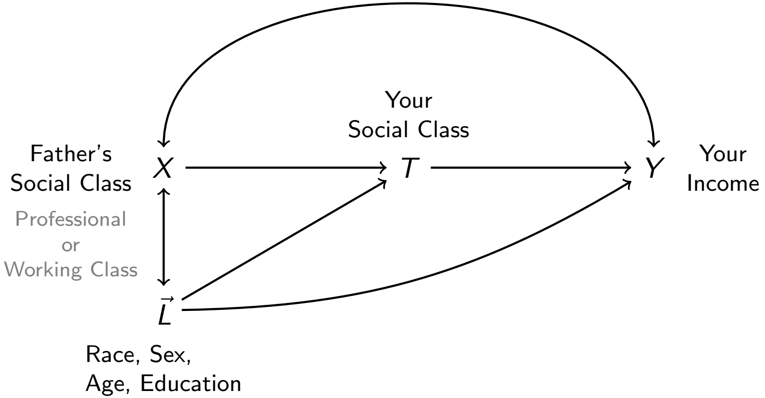

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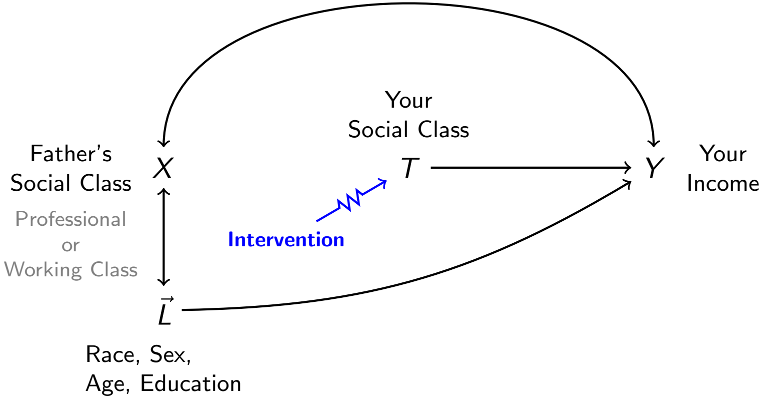

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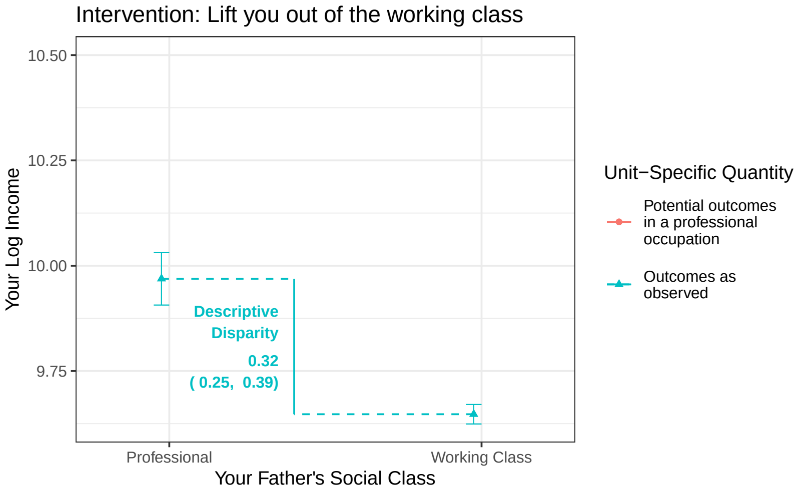

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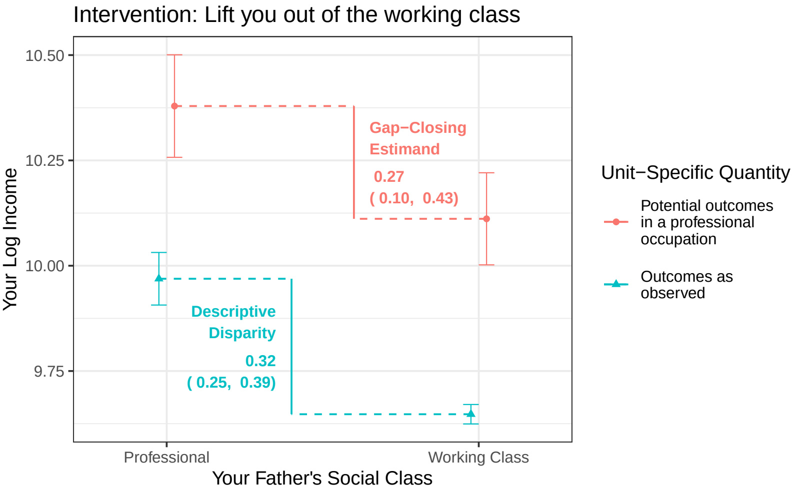

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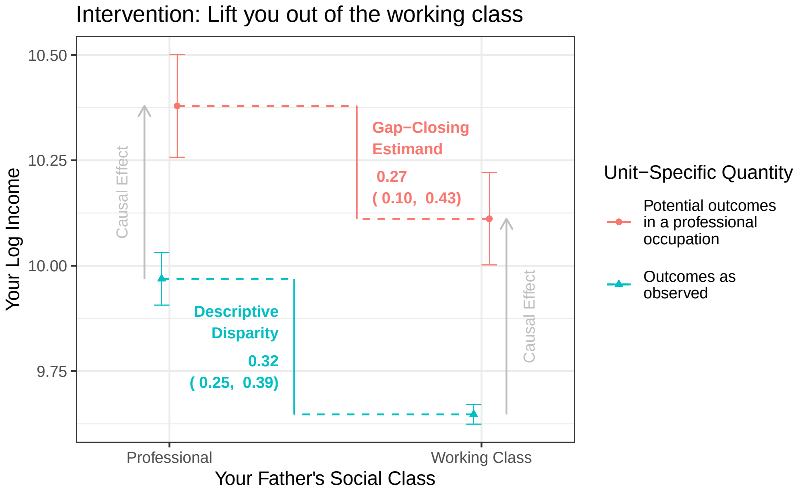
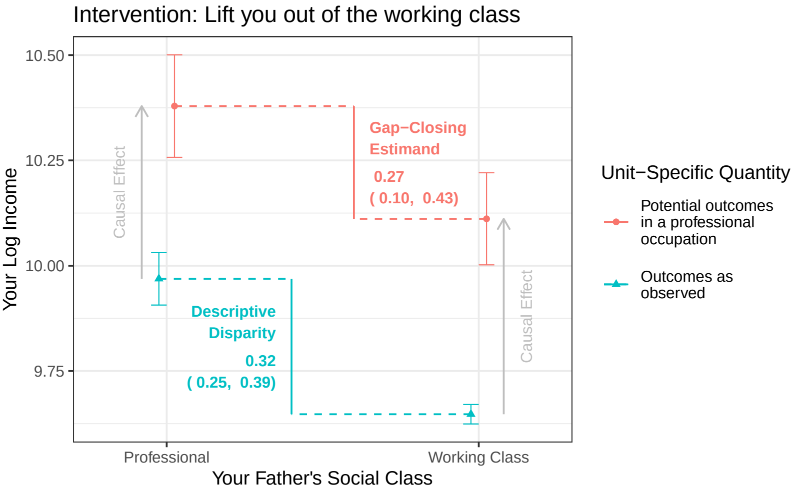
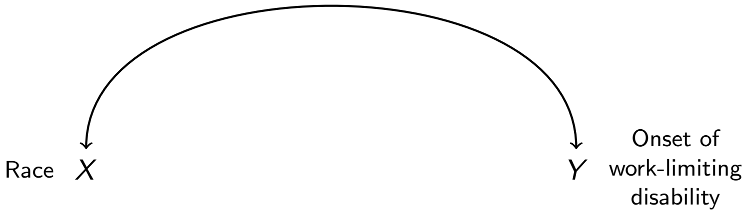


## Empirical Example 1: Economic Mobility

`plot_two_categories()`



## **Empirical Example 2**: Racial Disparities in Health



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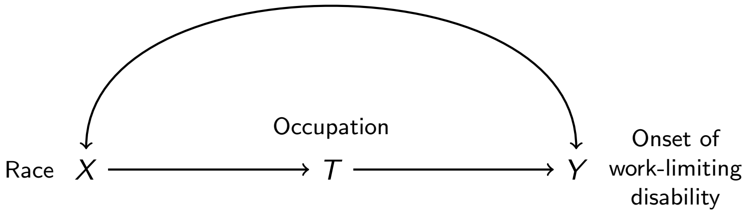

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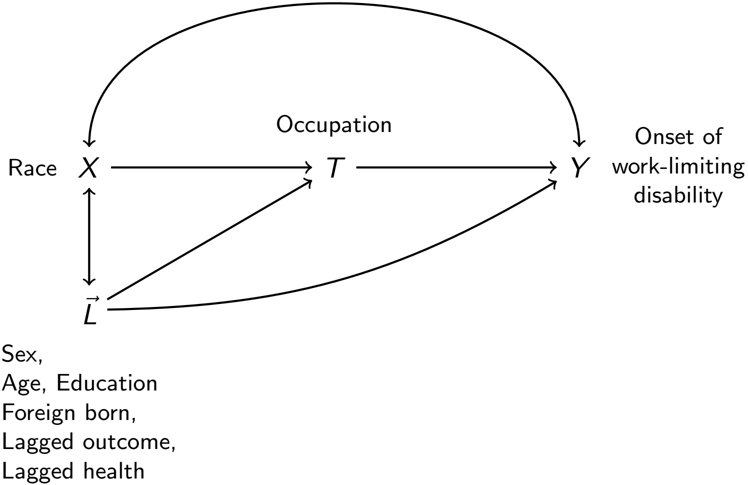

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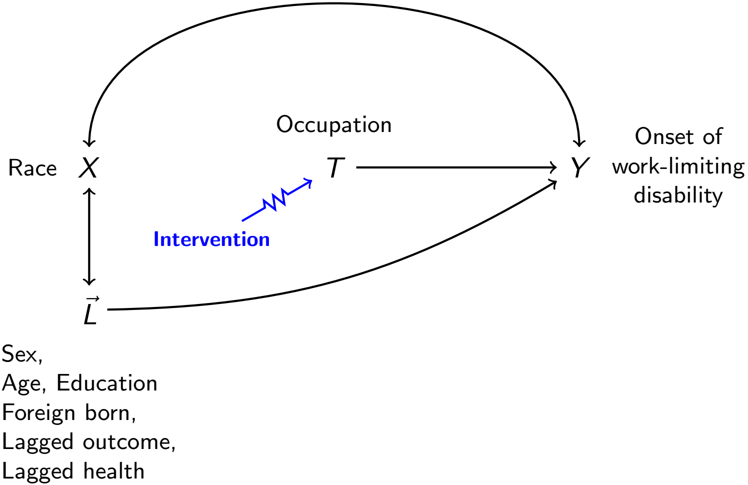

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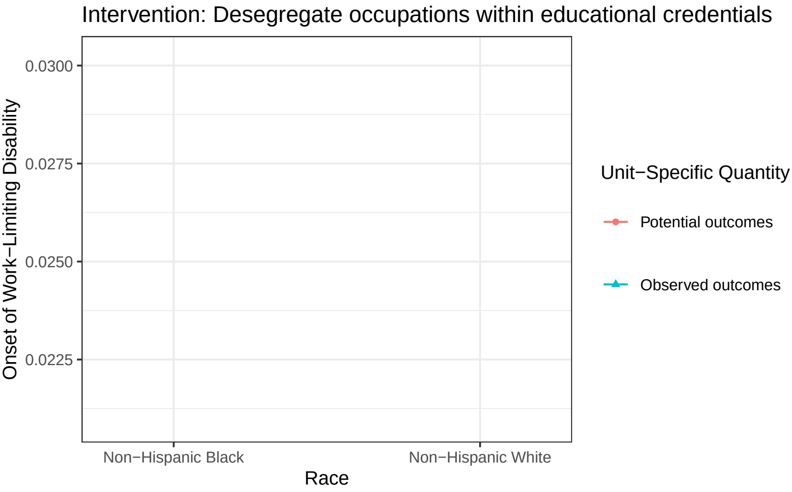

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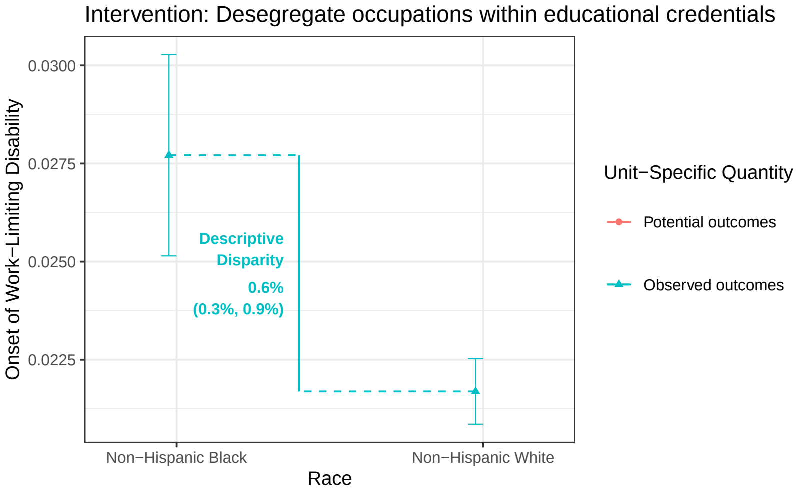

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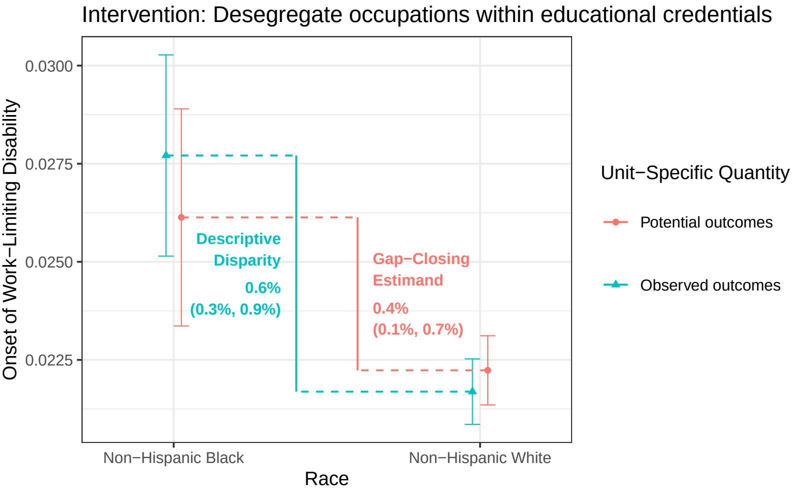

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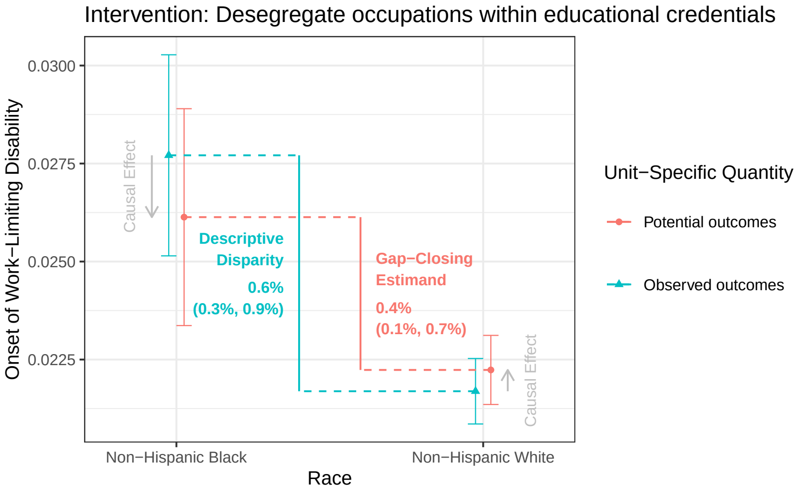

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The Black-white gap would close by more than one-fourth

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2023, Vol. 88(1) 154–188

DOI:10.1177/00031224221141887
journals.sagepub.com/home/asr
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## Higher Education and the Black-White Earnings Gap

Xiang Zhou[a] and Guanghui Pan[b]

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We could **intervene** to promote college completion

The gap would close by more than half for men,
but not for women

# Impact: We can now study gaps in a **new way**

EMPIRICAL ARTICLE

CHILD DEVELOPMENT

**Environmental inequality and disparities in school readiness: The role of neurotoxic lead**

**Jared N. Schachner**[1] | **Geoffrey T. Wodtke**[2]

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EMPIRICAL ARTICLE

CHILD DEVELOPMENT

**Environmental inequality and disparities in school readiness: The role of neurotoxic lead**

Jared N. Schachner[1] | Geoffrey T. Wodtke[2]

There are **gaps** in vocabulary skills by race and class

We could **intervene** to equalize exposure to lead

Gaps would close by 15–25%

# The Gap-Closing Estimand

A causal approach to study interventions that close disparities across social categories

- Past work: Causal decomposition analysis
- Define the estimand
  - what is the treatment?
  - what is the scope of the intervention?
- Identify the estimand
  - choose a sufficient adjustment set
- Estimate
  - by outcome modeling
  - by weighting
  - by doubly robust estimation
- Produce software
- Impact: Others using these ideas

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| Counterfactual slopes | $\frac{\text{Cov}(Y^1, X)}{\text{Var}(X)}$ for continuous $X$ (Yu & Zhao 2024) |

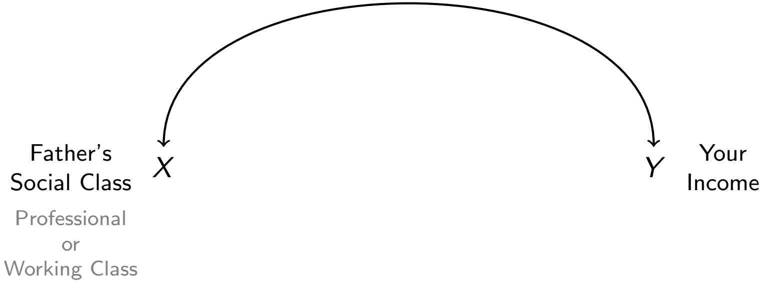
# Thanks!

Ian Lundberg
ianlundberg.org
ianlundberg@ucla.edu

More about this project with a code tutorial:
ilundberg.github.io/gapclosing

# Appendix

## **Empirical Example 1**: Economic Mobility



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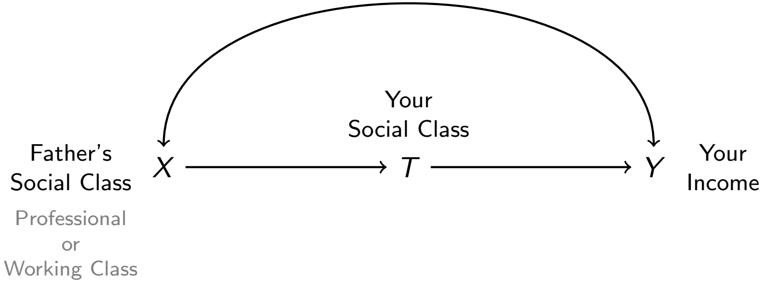

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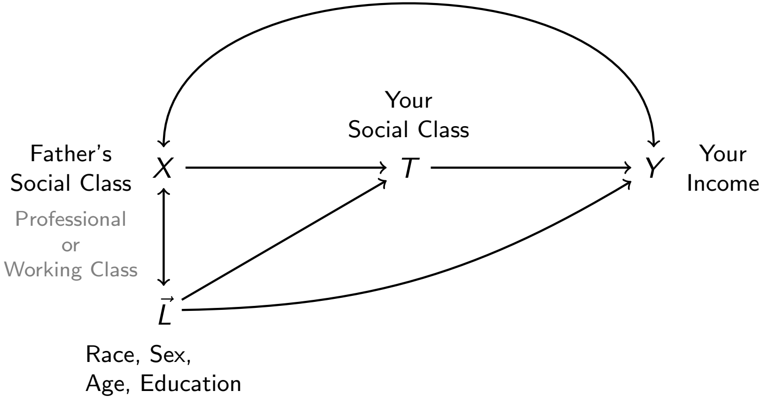

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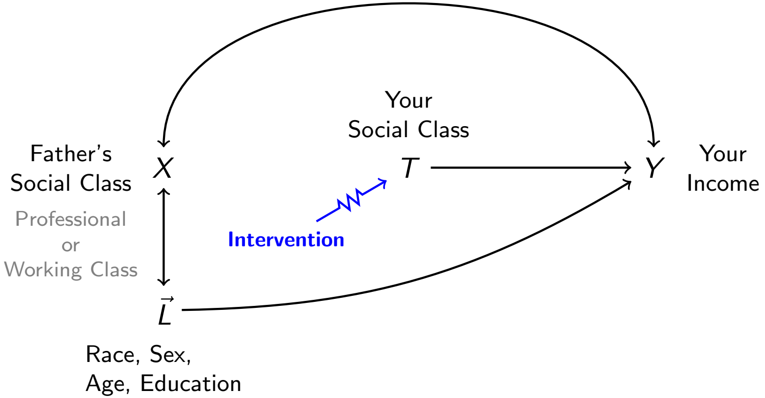

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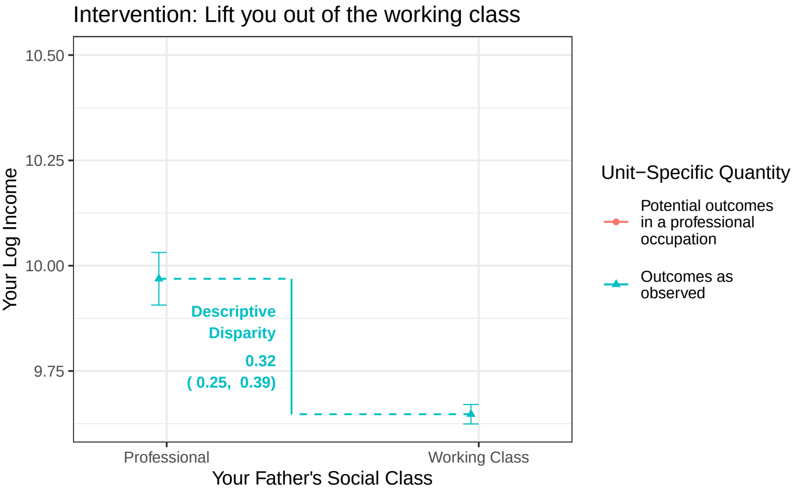

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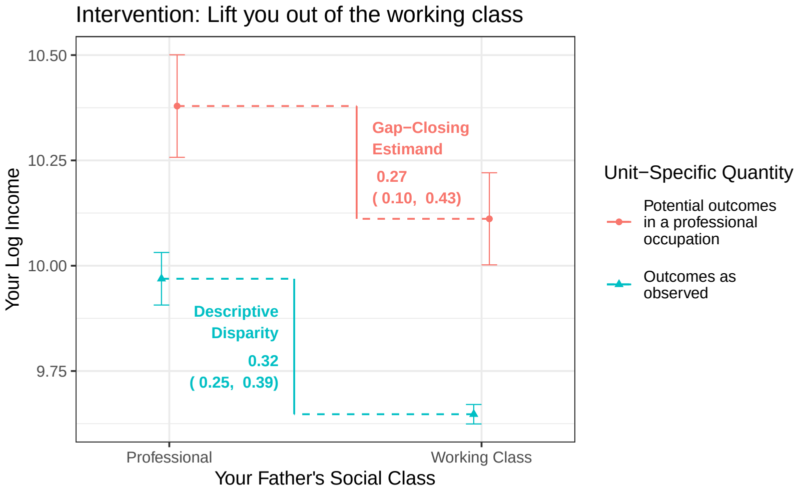

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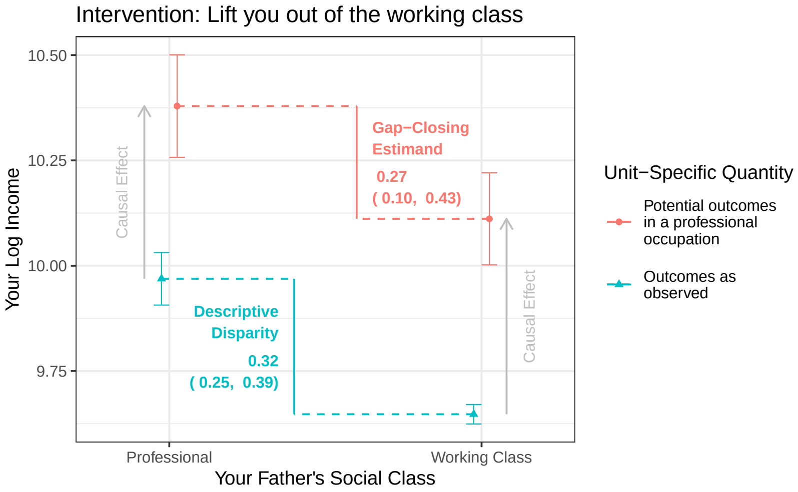

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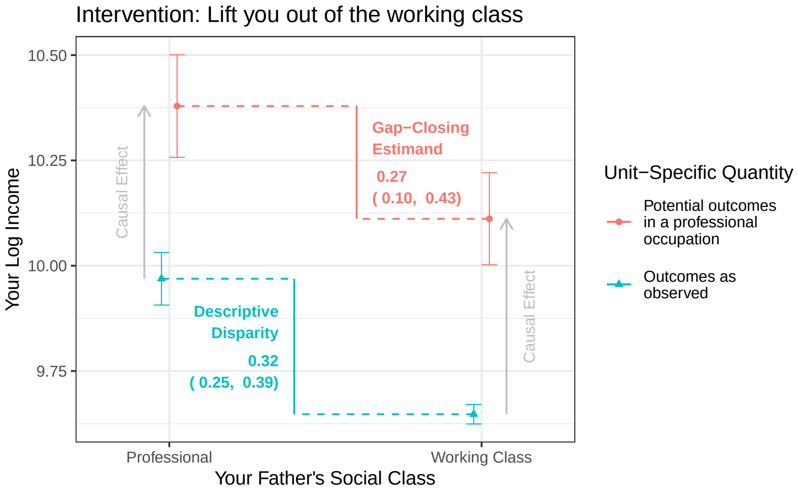
`plot_two_categories()`



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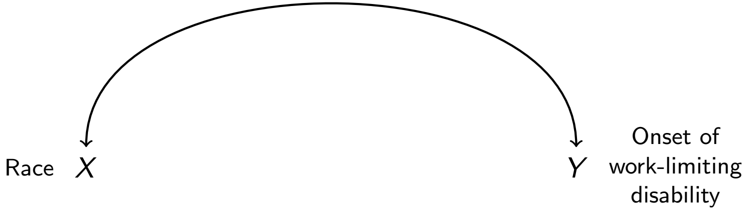

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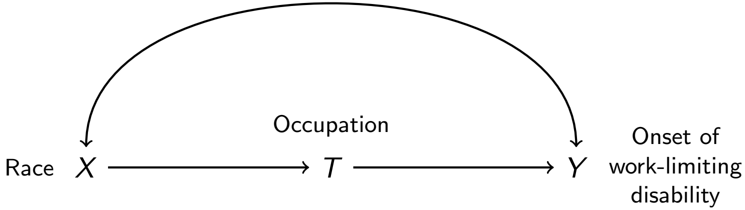

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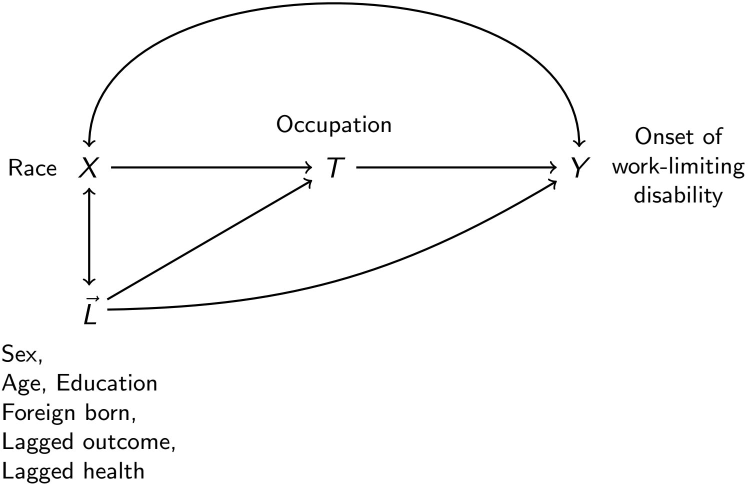

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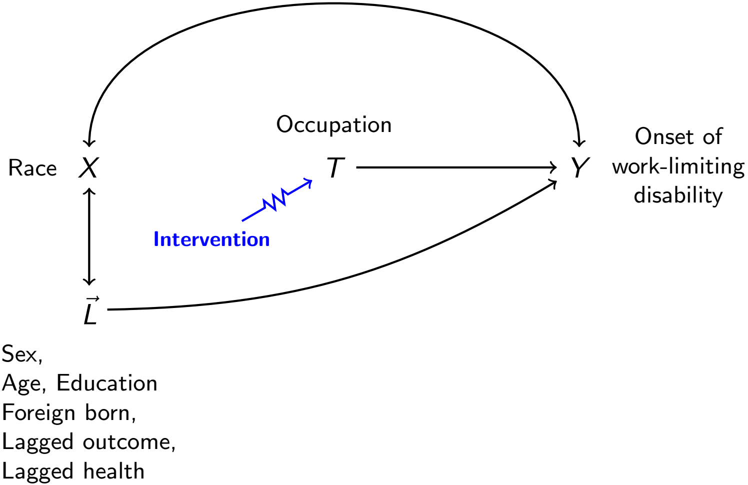

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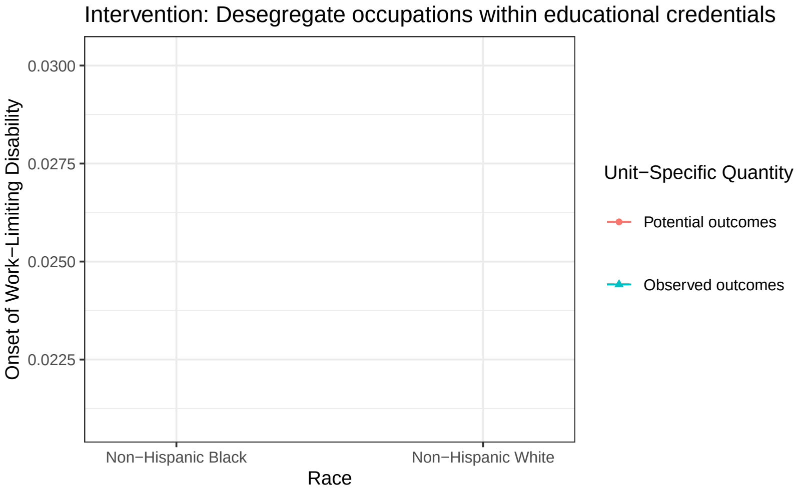

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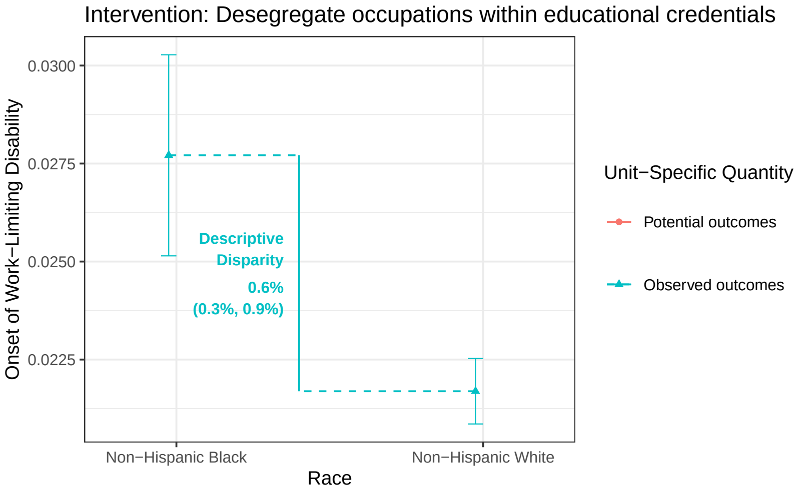

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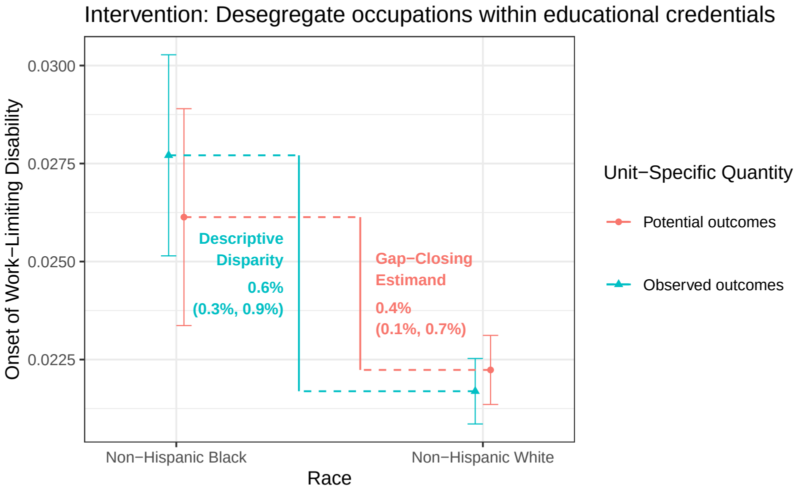

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