### The gap-closing estimand

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

#### Ian Lundberg

## UCLA ianlundberg@ucla.edu

Research reported in this publication was supported by The Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health under Award Number P2CHD047879. Replication code is available at github.com/ilundberg/replication

Methodological limitations

Methodological produce Narrow questions

Methodological produce Narrow questions

If we change the way we ask research questions, advances in both theory and methods are possible.

The gap-closing estimand:

General method

The gap-closing estimated

The disparity across social categories that would persist if we equalized a treatment



The gap-closing estimand: General method The gap-closing estimand:
The disparity across social categories that would persist if we equalized a treatment

Specific Occupational segregation contributes to racial disparities in health

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

Introduction Disparities call for explanations

Data Current Population Survey

Causal Question How an intervention would close a gap

Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

Ian Lundberg

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

→ Introduction

Disparities call for explanations

Data

Current Population Survey

Causal Question

How an intervention would close a gap Causal assumptions and predictive tools

Estimation Results

Partially closing a gap in health

**Broadening out** 

A framework for quantitative methodology

lan Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion



The Gap-Closing Estimand: A Causal Approach to Study Interventions That Close Disparities Across Social Categories

Results

Discussion

lan Lundberg Introduction Data Causal Question Estimation

Working Professional Class Class





#### Men Women

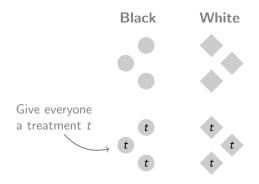


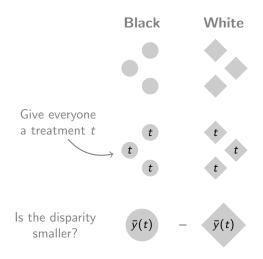


#### Black White









The Gap-Closing Estimand:
A Causal Approach to Study Interventions
That Close Disparities Across Social Categories

Ian Lundberg



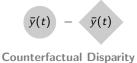


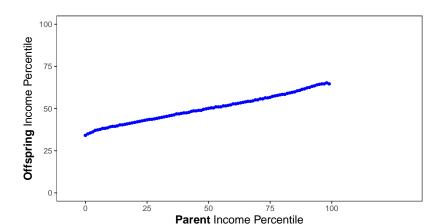


Discussion

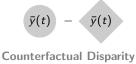
Counterfactual Disparity

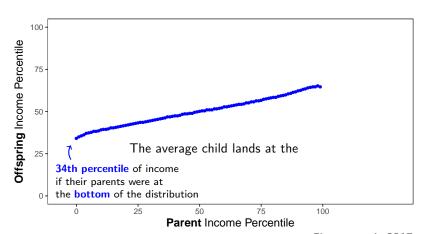




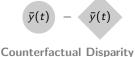




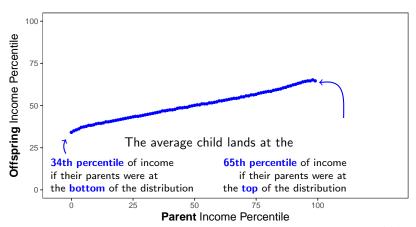




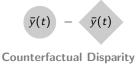


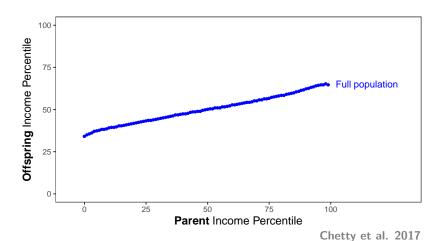






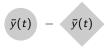






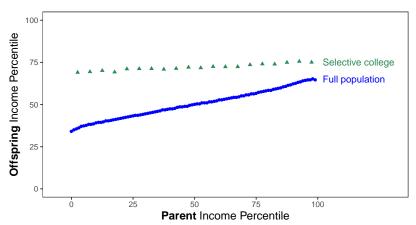






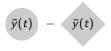
Treatment

Counterfactual Disparity



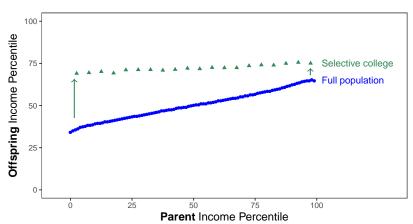




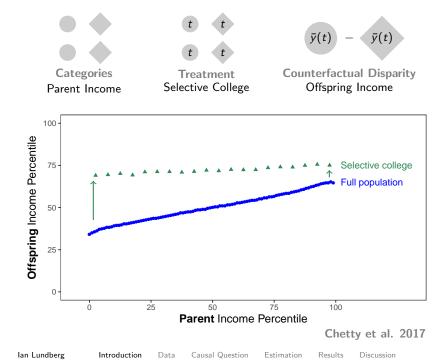


Treatment

**Counterfactual Disparity** 



 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



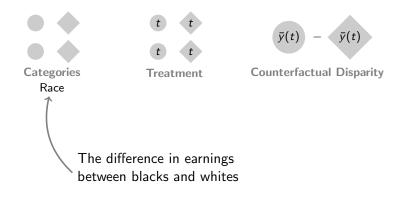






Discussion

Counterfactual Disparity

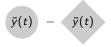


- Western 2006:12

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion







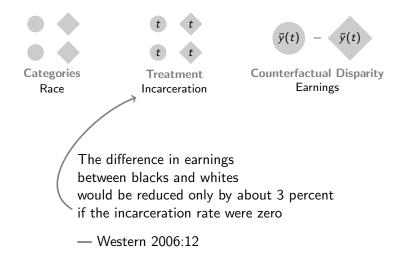
Treatment

Counterfactual Disparity Earnings

The difference in earnings between blacks and whites would be reduced only by about 3 percent if the incarceration rate were zero

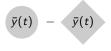
- Western 2006:12

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion









Counterfactual Disparity Earnings

The difference in earnings between blacks and whites would be reduced only by about 3 percent if the incarceration rate were zero

— Western 2006:12

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



$$ar{y}(t) - ar{y}(t)$$
Counterfactual Disparity

We often want to know if **intervening** on a treatment variable would close gaps

Jackson & Vanderweele 2018





Counterfactual Disparity

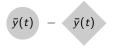
We often want to know if **intervening** on a treatment variable would close gaps

Would racial disparities in health narrow if we eliminated occupational segregation?

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion







Treatment

**Counterfactual Disparity** 

We often want to know if **intervening** on a treatment variable would close gaps

Would racial disparities in health narrow if we eliminated occupational segregation?







Treatment Co

Counterfactual Disparity Health

We often want to know if **intervening** on a treatment variable would close gaps

Would racial disparities in health narrow if we eliminated occupational segregation?









tegories Treatment Race Occupation

Counterfactual Disparity Health

We often want to know if **intervening** on a treatment variable would close gaps

Would racial disparities in health narrow if we eliminated occupational segregation?

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



Image Source: Wikipedia



Image Source: National Park Service

Racial inequality at work affects racial disparities in health

We know

We know Specific occupations pose substantial hazards

— "Occupational health"

Buchanan et al. 2010, Lowry et al. 2010, Fleischer et al. 2013, Holmes 2013

We

Specific occupations pose substantial hazards

— "Occupational health"

know People of color often hold hazardous occupations

We know Specific occupations pose substantial hazards

— "Occupational health"

People of color often hold hazardous occupations

Adjusting for occupation reduces the coefficient on race

Meyer 2014, Fujishiro et al. 2017

We know Specific occupations pose substantial hazards
— "Occupational health"

People of color often hold hazardous occupations

Adjusting for occupation reduces the coefficient on race

These studies **describe** the world as it exists

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

We know Specific occupations pose substantial hazards
— "Occupational health"

People of color often hold hazardous occupations

Adjusting for occupation reduces the coefficient on race

These studies describe the world as it exists

Disparities among subpopulations

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

We know Specific occupations pose substantial hazards
— "Occupational health"

People of color often hold hazardous occupations

Adjusting for occupation reduces the coefficient on race

These studies describe the world as it exists

They do not **prescribe** how to fix the problem

Disparities among subpopulations

We know Specific occupations pose substantial hazards
— "Occupational health"

People of color often hold hazardous occupations

Adjusting for occupation reduces the coefficient on race

These studies **describe** the world as it exists

Disparities among subpopulations

They do not **prescribe** how to fix the problem

How disparities **would** change if occupations were allocated equitably

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

→ Introduction

Disparities call for explanations

Data

Current Population Survey

Causal Question

How an intervention would close a gap Causal assumptions and predictive tools

Estimation Results

Partially closing a gap in health

**Broadening out** 

A framework for quantitative methodology

lan Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

Introduction Disparities call for explanations

→ Data Current Population Survey

Causal Question How an intervention would close a gap

Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

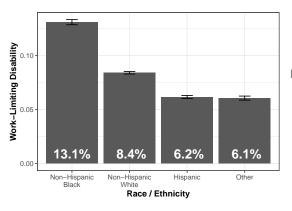
Discussion

Results

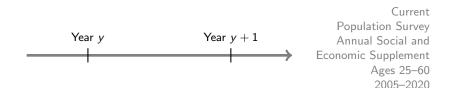
lan Lundberg Introduction Data Causal Question Estimation

Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

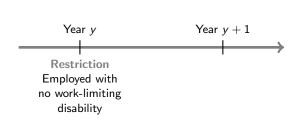
 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020



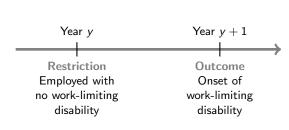
 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



Current Population Survey Annual Social and Economic Supplement Ages 25-60

2005-2020

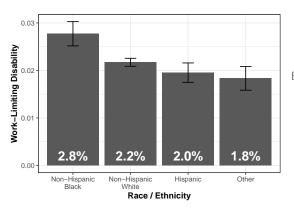
Introduction Causal Question Estimation Ian Lundberg Data Results Discussion



Current
Population Survey
Annual Social and
Economic Supplement
Ages 25–60
2005–2020

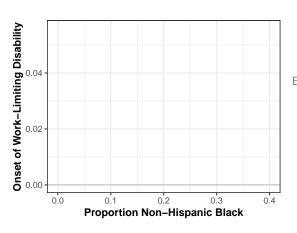
 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

#### **Onset of Work-Limiting Disability**



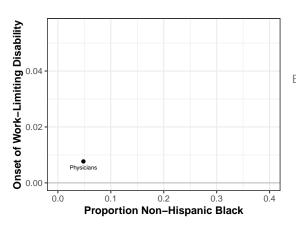
Current
Population Survey
Annual Social and
Economic Supplement
Ages 25–60
2005–2020

Employed last year No disability last year



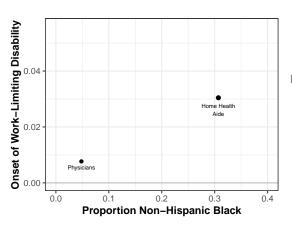
Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

> Employed last year No disability last year



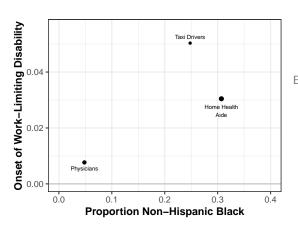
Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

> Employed last year No disability last year



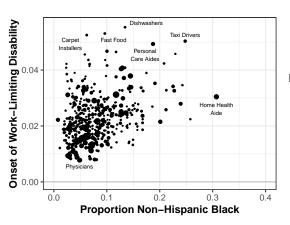
Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

> Employed last year No disability last year



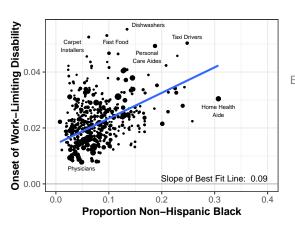
Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

> Employed last year No disability last year



Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

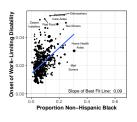
> Employed last year No disability last year



Current Population Survey Annual Social and Economic Supplement Ages 25-60 2005-2020

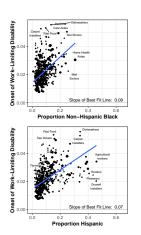
Employed last year No disability last year

Ian Lundberg Introduction Causal Question Estimation Data Results Discussion



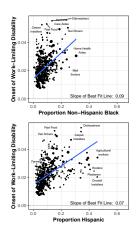
Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

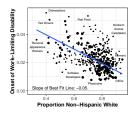
> Employed last year No disability last year



Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

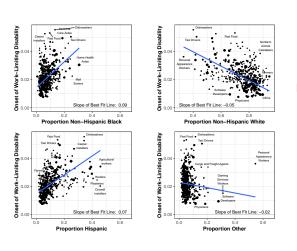
> Employed last year No disability last year







Employed last year No disability last year



Current Population Survey Annual Social and Economic Supplement Ages 25–60 2005–2020

> Employed last year No disability last year

Ian Lundberg

Introduction

Data

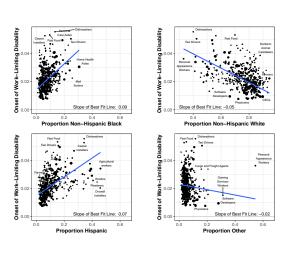
Causal Question

Estimation

Results

Discussion

### To what degree does occupational segregation contribute to racial health disparities?



Current Population Survey Annual Social and Economic Supplement Ages 25-60 2005-2020

> Employed last year No disability last year

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

**Introduction** Disparities call for explanations

→ Data Current Population Survey

-7 Data Current i opulation Survey

Causal Question How an intervention would close a gap

Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

Introduction Disparities call for explanations

Data Current Population Survey

→ Causal Question How an intervention would close a gap

Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

Person 1

Person 2

Person 3

Person 4

Person 5

Person 6

Person 7

Person 8

Data Causal Question Estimation Ian Lundberg Introduction

# Sales Administrative Home Health Supervisor Assistant Aid

Person 1

Person 2

Person 3

Person 4

Person 5

Person 6

Person 7

Person 8

## Administrative Home Health Assistant Aid

- Person 1
  Person 2

- Person 3
- Person 4
- Person 5
- Person 6
- Person 7
- Person 8

Sales

Supervisor

#### Sales Administrative Home Health Supervisor Assistant Aid

- Person 1
- Person 2
- Person 3
- Person 4
- Person 5
- Person 6
- Person 7
- Person 8

Sales Administrative Home Health Supervisor Assistant Aid Person 1 Person 2 Person 3 Person 4 Person 5 Person 6 Person 7 Person 8



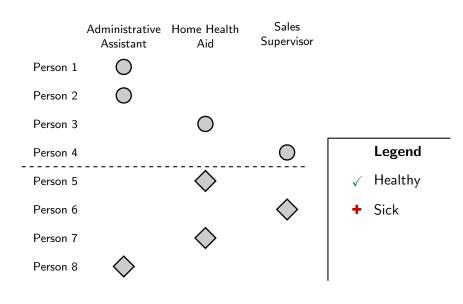
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$		
Person 2	$\bigcirc$		
Person 3		$\circ$	
Person 4			$\bigcirc$
Person 5		$\Diamond$	
Person 6			
Person 7			
Person 8			

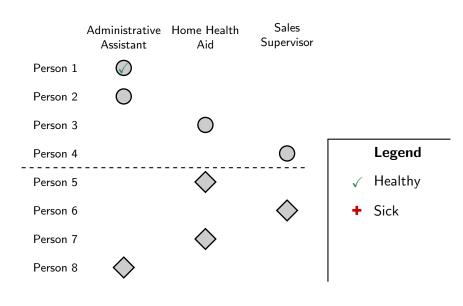
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$		
Person 2	$\bigcirc$		
Person 3		$\bigcirc$	
Person 4			$\bigcirc$
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7			
Person 8			

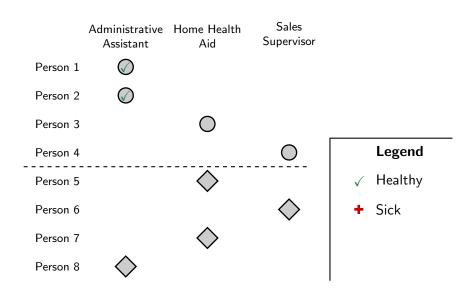
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$		
Person 2	$\bigcirc$		
Person 3		$\bigcirc$	
Person 4			$\bigcirc$
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8			

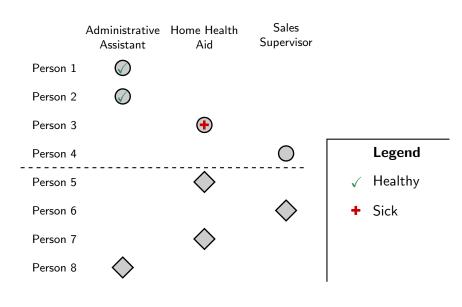
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$		
Person 2	$\bigcirc$		
Person 3		$\bigcirc$	
Person 4			$\bigcirc$
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		

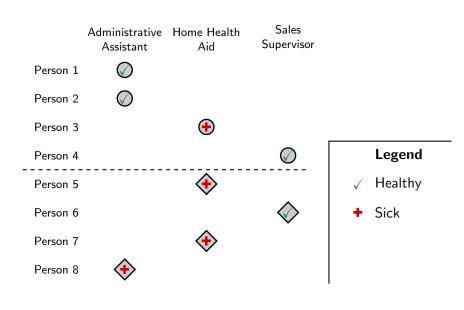
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$		
Person 2	$\bigcirc$		
Person 3		$\circ$	
Person 4			0
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		



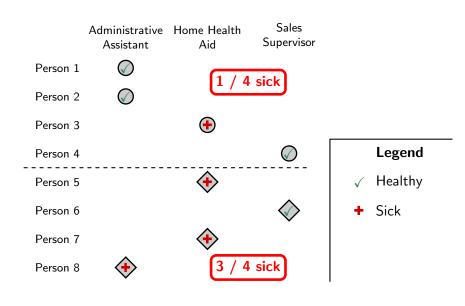






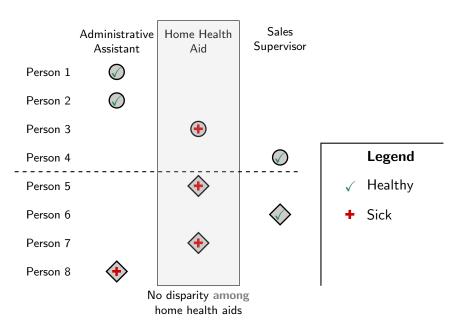


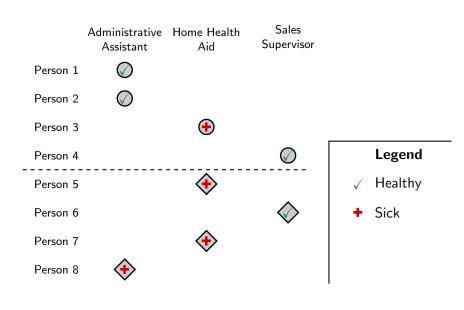


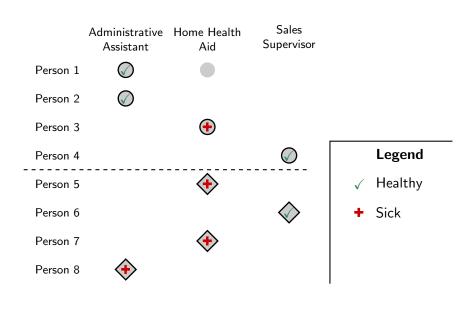


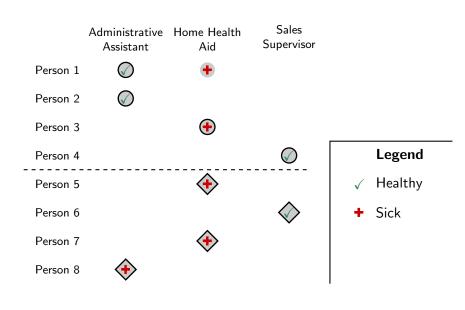
	Administrative Assistant	Home Health Aid	Sales Supervisor	
Person 1	$\bigcirc$			
Person 2	$\bigcirc$			
Person 3		<b>(+)</b>		
Person 4			$\bigcirc$	Legend
Person 5		<b>(+)</b>		√ Healthy
Person 6			$\Diamond$	+ Sick
Person 7		•		
Person 8	<b>(+)</b>			

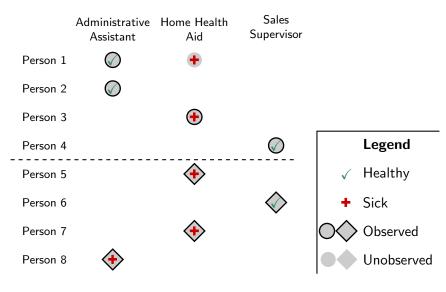
 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion





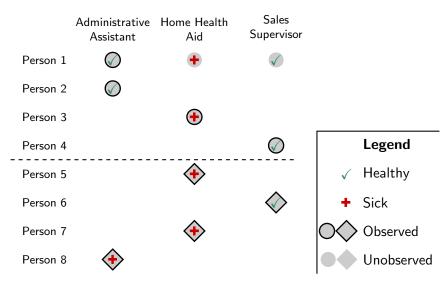




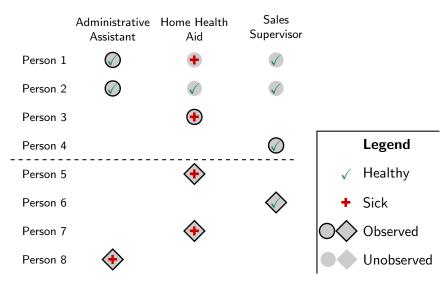


Imbens and Rubin 2015 Discussion

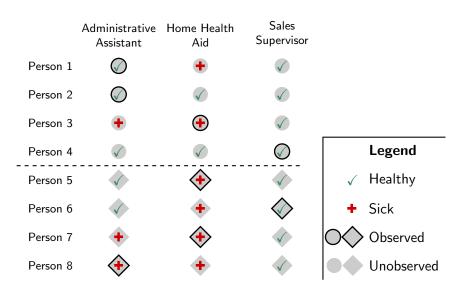
Results



Imbens and Rubin 2015



Imbens and Rubin 2015



Imbens and Rubin 2015

	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	$\bigcirc$	•	
Person 2	$\bigcirc$	$\checkmark$	$\checkmark$
Person 3	•	•	
Person 4	$\checkmark$	$\checkmark$	$\bigcirc$
Person 5	<b>♦</b>	•	<b>✓</b>
Person 6		+	$\Diamond$
Person 7	•	•	
Person 8	<b>(*)</b>	•	

Ian Lundberg Introduction Data Causal Question Estimation

		Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Perso	on 1		•	$\checkmark$	
Perso	on 2	$\bigcirc$	$\checkmark$	$\checkmark$	
Perso	on 3	•	•	$\checkmark$	
Perso	on 4	$\checkmark$	$\checkmark$		
Perso	on 5	<b>♦</b>	•	$\checkmark$	
Perso	on 6		+	$\Diamond$	
Perso	on 7	+	•		
Perso	on 8	•	+		

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Person 1	$\bigcirc$	•	$\checkmark$	1 / 3
Person 2		$\checkmark$	$\checkmark$	
Person 3	•	•	$\checkmark$	
Person 4	$\checkmark$	$\checkmark$	$\bigcirc$	
Person 5	<b>⋄</b>	<b>(+)</b>		
Person 6		+	$\Diamond$	
Person 7	+	<b>(+)</b>		
Person 8	<b>(*)</b>	+		

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Person 1		•	$\checkmark$	1 / 3
Person 2		$\checkmark$	$\checkmark$	0 / 3
Person 3	•	•	$\checkmark$	
Person 4	$\checkmark$	$\checkmark$	$\bigcirc$	
Person 5	<b>⋄</b>	•	<b>✓</b>	
Person 6		+	$\Diamond$	
Person 7	+	<b>(+)</b>		
Person 8	<b>(*)</b>	•	$\checkmark$	

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Person 1		•		1 / 3
Person 2		$\checkmark$	$\checkmark$	0 / 3
Person 3	•	•	$\checkmark$	2 / 3
Person 4	<b>✓</b>	$\checkmark$		
Person 5	<b>⋄</b>	<b>(+)</b>	<b>✓</b>	
Person 6		+	$\Diamond$	
Person 7	+	<b>(+)</b>		
Person 8	<b>(*)</b>	•	$\checkmark$	

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Person 1	$\bigcirc$	•	$\checkmark$	1 / 3
Person 2	$\bigcirc$		$\checkmark$	0 / 3
Person 3	•	•	$\checkmark$	2 / 3
Person 4	$\checkmark$	$\checkmark$		0 / 3
Person 5	<b>♦</b>	•	<b>√</b>	
Person 6		+	$\Diamond$	
Person 7	+	•		
Person 8	<b>(*)</b>	+		

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness
Person 1	$\bigcirc$	•	$\checkmark$	1 / 3
Person 2	$\bigcirc$	$\checkmark$	$\checkmark$	0 / 3
Person 3	•	•	$\checkmark$	2 / 3
Person 4	$\checkmark$		$\bigcirc$	0 / 3
Person 5	<b></b>	<b>+</b>	<b>✓</b>	1 / 3
Person 6		+	$\Diamond$	1 / 3
Person 7	+	<b>(+)</b>		2 / 3
Person 8	<b>(+)</b>	+		2 / 3

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness	
Person 1	$\bigcirc$	•	$\checkmark$	1 / 3	
Person 2	$\bigcirc$		$\checkmark$	0 / 3	$\frac{3}{12}$
Person 3	•	•	$\checkmark$	2 / 3	12
Person 4	$\checkmark$	<b>✓</b>		0 / 3	
Person 5	<b>♦</b>	•	<b>✓</b>	1 / 3	
Person 6		+	$\Diamond$	1 / 3	
Person 7	+	<b>(+)</b>		2 / 3	
Person 8	•	+		2 / 3	

Ian Lundberg Introduction Data Causal Question Estimation

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness	
Person 1	$\bigcirc$	•	$\checkmark$	1 / 3	
Person 2	$\bigcirc$		$\checkmark$	0 / 3	3
Person 3	•	•	$\checkmark$	2 / 3	$\left(\begin{array}{c} \frac{3}{12} \end{array}\right)$
Person 4	$\checkmark$			0 / 3	
Person 5	<b></b>	<b>(+</b> )	<b>♦</b>	1 / 3	
Person 6		+	$\Diamond$	1 / 3	6
Person 7	+	<b>(+)</b>		2 / 3	$\left\langle \frac{6}{12} \right\rangle$
Person 8	•	+		2 / 3	

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Sickness	
Person 1		•	$\checkmark$	1 / 3	
Person 2		$\checkmark$	$\checkmark$	0 / 3	$\left(\begin{array}{c} 3\\ \overline{12} \end{array}\right)$
Person 3	•	•	$\checkmark$	2 / 3	$\overline{12}$
Person 4	<b>✓</b>	$\checkmark$	$\bigcirc$	0 / 3	
Person 5	<b>⋄</b>	•	<b>✓</b>	1 / 3	
Person 6		+	$\Diamond$	1 / 3	6
Person 7	+	•		2 / 3	$\left\langle \frac{6}{12} \right\rangle$
Person 8	<b>(+)</b>	+	<b>~</b>	2 / 3	
	Counterfact	tual Disparity:	$\left\langle \frac{6}{12} \right\rangle$ -	$\underbrace{\frac{3}{12}} = \frac{3}{12}$	=25%

Ian Lundberg

Introduction

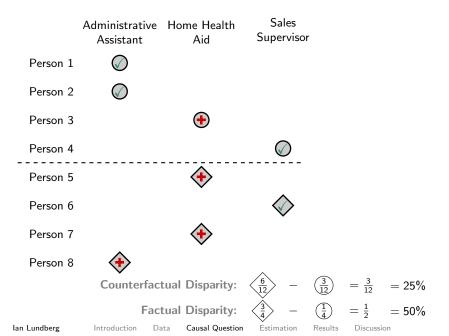
Data

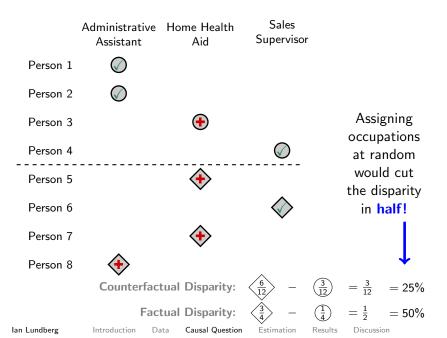
Causal Question

Estimation

Results

Discussion





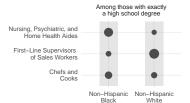
#### Factual Assignment Rule

Among those with exactly a high school degree



on–Hispa Black

#### Factual Assignment Rule



#### Factual Assignment Rule

Among those with exactly a high school degree

Nursing, Psychiatric, and Home Health Aides

First-Line Supervisors of Sales Workers

Chefs and Cooks

Non-Hispanic Non-Hispanic Black

White

Among those with exactly a high school degree

Equalize occupational assignment

lan Lundberg Introduction Data Causal Question Estimation Results Discussion

#### Factual Assignment Rule Among those with exactly

a high school degree

Non-Hispanic Non-Hispanic Black White

#### Counterfactual Assignment Rule

Among those with exactly a high school degree



Non-Hispanic Non-Hispanic Black White

Data Causal Question

Results

Discussion

Nursing, Psychiatric, and Home Health Aides First-Line Supervisors of Sales Workers

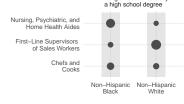
> Chefs and Cooks

Equalize

occupational

assignment

# Factual Assignment Rule Among those with exactly



occupational assignment

within education

#### Counterfactual Assignment Rule

Among those with exactly a high school degree



Non-Hispanic Non-Hispanic Black White

lan Lundberg

Introduction

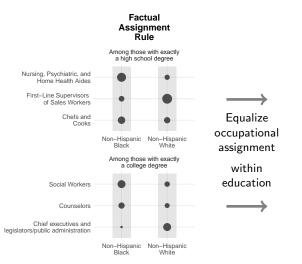
Data

Causal Question

Estimation

Results

Discussion



#### Counterfactual Assignment Rule

Among those with exactly a high school degree

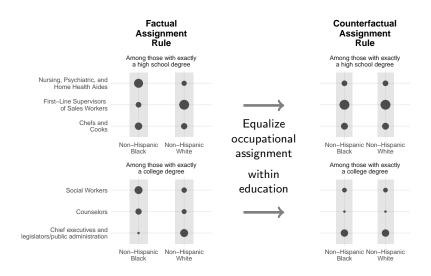


Non-Hispanic Non-Hispanic Black White

Among those with exactly a college degree

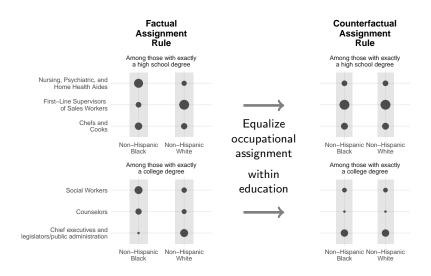


Non-Hispanic Non-Hispanic Black White



## Equalizing within education is equitable

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



## Equalizing within education is equitable but also realistic

lan Lundberg Introduction Data Causal Question Estimation Results Discussion

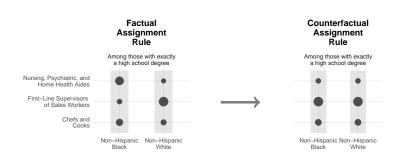
We now have a way to think about what **would** happen if occupations were **assigned differently** 

	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0	?	?
Person 2	0	?	?
Person 3	?	0	?
Person 4	?	?	0
Person 5	?	$\Diamond$	?
Person 6	?	?	$\Diamond$
Person 7	?	$\Diamond$	?
Person 8	$\Diamond$	?	?

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

We now have a way to think about what **would** happen if occupations were **assigned differently** 

We have a way to think about equitable assignment to occupations



We now have a way to think about what would happen if occupations were assigned differently

We have a way to think about **equitable assignment** to occupations

But that seems to suggest a **grand claim**: what would happen under a structural intervention to desegregate occupations

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

Black-white pay gap "if the incarceration rate were zero." - Western (2006:127)

Black-white pay gap "if the incarceration rate were zero."

— Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'."

— Zhou (2019:466).

Black-white pay gap "if the incarceration rate were zero."

— Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Causal Question

Sex pay gap if "sex segregation...were abolished."

— Petersen and Morgan (1995:338).

Equalize for everyone at once

```
Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)
```

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished."

— Petersen and Morgan (1995:338).

lan Lundberg Introduction Data Causal Question Estimation Results Discussion

Equalize for everyone at once

```
Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)
```

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished." — Petersen and Morgan (1995:338).

Link & Phelan 1995, Raftery & Hout 1993, Lucas 2001

Local interpretation

Equalize for everyone at once

Equalize for one unit at a time

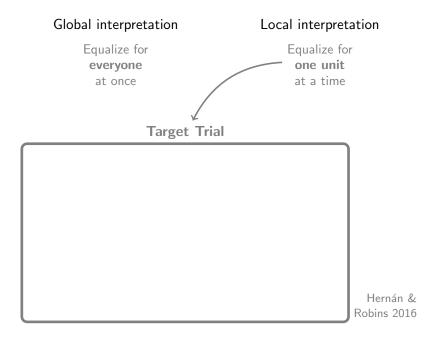
Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)

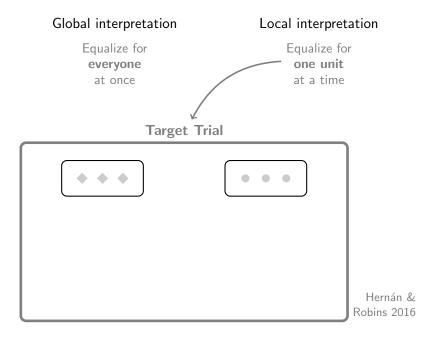
Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

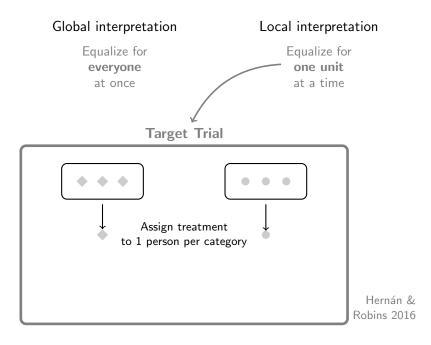
— Znou (2019:400).

Sex pay gap if "sex segregation...were abolished."

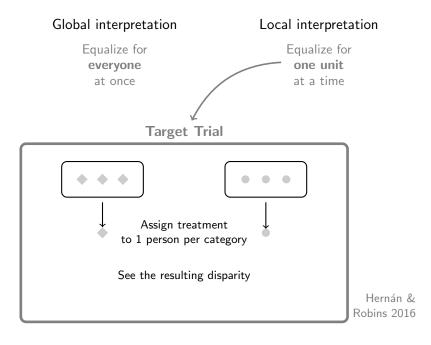
— Petersen and Morgan (1995:338).



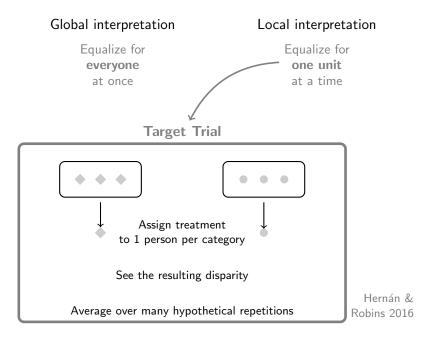




lan Lundberg Introduction Data Causal Question Estimation Results Discussion



Ian LundbergIntroductionDataCausal QuestionEstimationResultsDiscussion



Ian LundbergIntroductionDataCausal QuestionEstimationResultsDiscussion

Local interpretation

Equalize for everyone at once

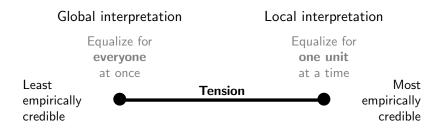
Equalize for one unit at a time

Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished."

— Petersen and Morgan (1995:338).

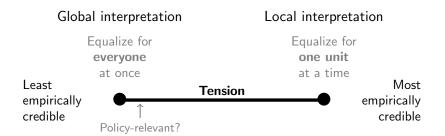


Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished."

— Petersen and Morgan (1995:338).

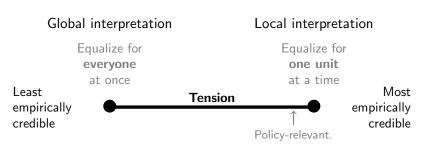


Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'."

— Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished." — Petersen and Morgan (1995:338).



Black-white pay gap "if the incarceration rate were zero." — Western (2006:127)

Class origin pay gap in "a utopian world of 'college for all'." — Zhou (2019:466).

Sex pay gap if "sex segregation...were abolished." — Petersen and Morgan (1995:338).

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

## Structure of the talk

Introduction Disparities call for explanations

Data Current Population Survey

→ Causal Question How an intervention would close a gap

Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

## Structure of the talk

Introduction Disparities call for explanations

Data Current Population Survey

Causal Question How an intervention would close a gap

→ Estimation Causal assumptions and predictive tools

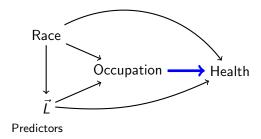
Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

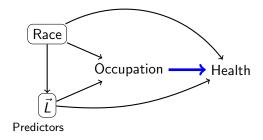
lan Lundberg Introduction Data Causal Question Estimation

Results

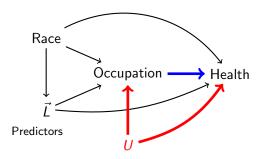
Discussion



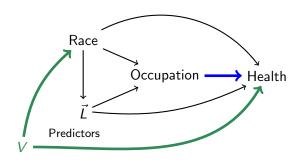
Pearl 2009, Morgan & Winship 2015, Hernán & Robins 2020



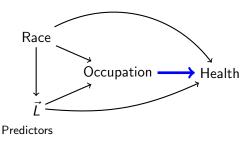
 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion

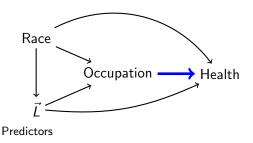


Ian LundbergIntroductionDataCausal QuestionEstimationResultsDiscussion



A gap-closing estimand is agnostic about the causal effect of race

Ian Lundberg Introduction Data Causal Question Estimation Results Discussion



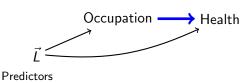
A gap-closing estimand is  ${\bf agnostic}$  about the causal effect of race

— Race can affect everything

Williams et al. 2019

Ian LundbergIntroductionDataCausal QuestionEstimationResultsDiscussion

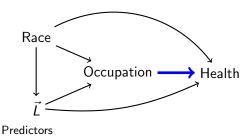




A gap-closing estimand is agnostic about the causal effect of race

- Race can affect everything
- Race can have no causal effects

Greiner & Rubin 2011

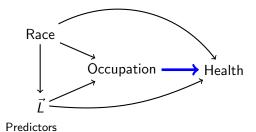


A gap-closing estimand is agnostic about the causal effect of race

- Race can affect everything
- Race can have no causal effects
- The effect of race can be philosophically complex

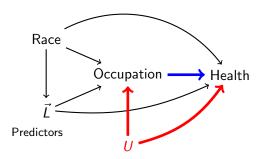
Sen & Wasow 2016, Kohler-Hausmann 2018

**Identification:** We have to impute the outcome each person i would realize in each occupation t

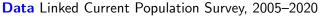


lan Lundberg Introduction Data Causal Question Estimation Results Discussion

**Identification:** We have to impute the outcome each person i would realize in each occupation t



Ian LundbergIntroductionDataCausal QuestionEstimationResultsDiscussion



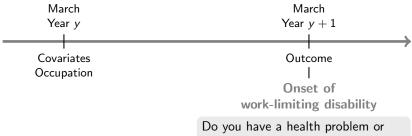


Ian Lundberg In:



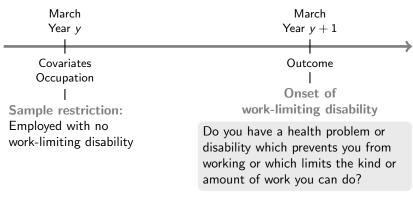
Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



lan Lundberg Introduction Data Causal Question Estimation Results Discussion



Predictors:

Race, Sex Self-rated health

Education Age Foreign born Year

work-limiting disability

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

lan Lundberg Introduction Data Causal Question Estimation Results Discussion



**Predictors:** 

Race. Sex

Self-rated health

Education Age Foreign born

work-limiting disability

Year

**Credibility Check:** 

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

Ian Lundberg Introduction Data Causal Question Estimation Results Discussion



**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

> Administrative Home Health Assistant Aid

Woman 1



Woman 2



Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

> Administrative Home Health Assistant Aid

Woman 1



Woman 2



Ian Lundberg

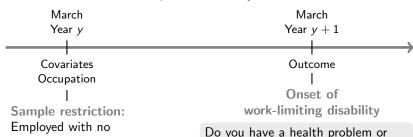
Introduction

Data

Causal Question

Estimation

Results



**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black Both high school graduates

Woman 1

Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?



Woman 2

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black
Both high school graduates

Neither foreign born

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

> Administrative Home Health Assistant Aid

Woman 2

Woman 1



Ian Lundberg

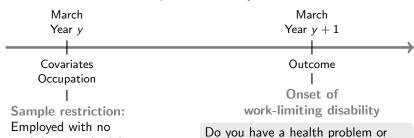
Introduction

Data

Causal Question

Estimation

Results



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?

Woman 1

Woman 2



Estimation

Results



work-limiting disability

#### **Predictors:**

Race, Sex Self-rated health

Education Age Foreign born Year

# **Credibility Check:**

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010 disability which prevents you from working or which limits the kind or amount of work you can do?

> Administrative Home Health Assistant Aid

Woman 1

Woman 2



Ian Lundberg

Introduction

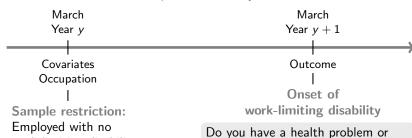
Data

Causal Question

Estimation

Results

Discus



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1

Woman 2

Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?

 $\Diamond$ 

 $\Diamond$ 

Ian Lundberg

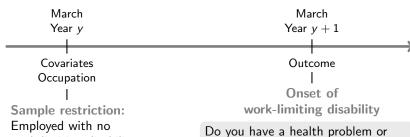
Introduction

Data

Causal Question

Estimation

Results



work-limiting disability

**Predictors:** 

Race. Sex Self-rated health

Education Age Foreign born Year

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1

Assistant

disability which prevents you from

working or which limits the kind or

Administrative Home Health

amount of work you can do?

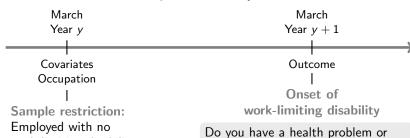
Woman 2



Discussion

Aid

Ian Lundberg Introduction Data Causal Question Estimation Results



work-limiting disability

**Predictors:** 

Race, Sex Self-rated health

Education Age Foreign born Year

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010 Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?

Woman 1



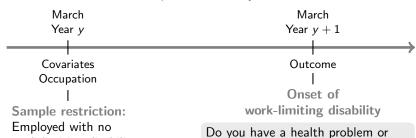


**(+)** 

ld in 2010 Woman 2

Estimation R

Results



**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1

Woman 2

Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?



Ian Lundberg

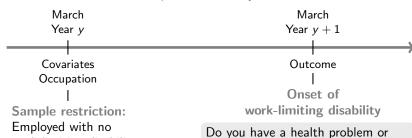
Introduction

Data

Causal Question

Estimation

Results



**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

# **Credibility Check:**

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1



Woman 2



Administrative

Assistant





Home Health

Aid

Ian Lundberg

Introduction

Data

Causal Question

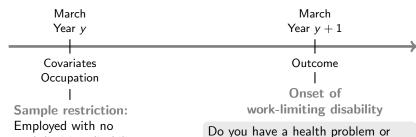
Estimation

Results

disability which prevents you from

working or which limits the kind or

amount of work you can do?



**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

**Credibility Check:** 

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1

Woman 2

Administrative Home Health Assistant Aid

disability which prevents you from

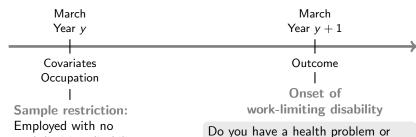
working or which limits the kind or

amount of work you can do?









**Predictors:** Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

# **Credibility Check:**

Both Black Both high school graduates Neither foreign born Both report excellent health Both 30 years old in 2010

Woman 1

Woman 2

Administrative Home Health Assistant Aid

disability which prevents you from

working or which limits the kind or

amount of work you can do?







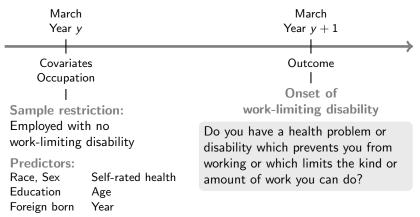
Ian Lundberg

Introduction

Data

Causal Question

Estimation



Supplemental restrictions:

 Ian Lundberg
 Introduction
 Data
 Causal Question
 Estimation
 Results
 Discussion



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

# Supplemental restrictions:

#### No difficulty with

hearing walking

vision performing basic duties remembering caring for personal needs

lan Lundberg

Introduction

Data

Causal Question

Estimation

Results



Predictors: Race. Sex

Self-rated health

Education Age Foreign born Year

work-limiting disability

Do you have a health problem or disability which prevents you from working or which limits the kind or amount of work you can do?

# Supplemental restrictions:

#### No difficulty with

hearing walking

vision performing basic duties remembering caring for personal needs

and

Never left a job for health reasons

Ian Lundberg

Introduction

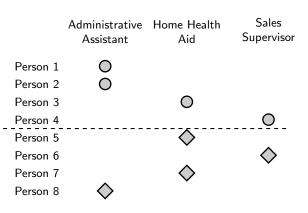
Data

Causal Question

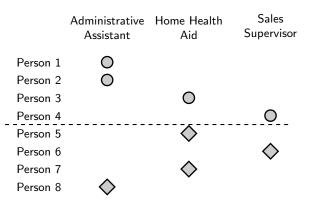
Estimation

Results

	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0	?	?
Person 2	0	?	?
Person 3	?	0	?
Person 4	?	?	0
Person 5	?	$\Diamond$	?
Person 6	?	?	$\Diamond$
Person 7	?	$\Diamond$	?
Person 8	$\Diamond$	?	?



Prediction Function





	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0		
Person 2	0		
Person 3		0	
Person 4			0
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0		
Person 2	0		
Person 3		0	
Person 4			0
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0		
Person 2	0		
Person 3		0	
Person 4			0
Person 5		<b>\rightarrow</b>	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	0		
Person 2	0		
Person 3		0	
Person 4			0
Person 5		$\Diamond$	
Person 6			$\Diamond$
Person 7		$\Diamond$	
Person 8	$\Diamond$		



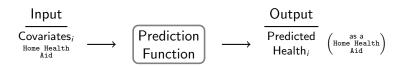
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø		
Person 2	Ø		
Person 3	ŷ	0	
Person 4	ŷ		0
Person 5	ŷ	$\Diamond$	
Person 6	ŷ		$\Diamond$
Person 7	ŷ	$\Diamond$	
Person 8	<b>\$</b>		



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	<b>Ø</b>		
Person 2	Ø		
Person 3	ŷ	0	
Person 4	ŷ		0
Person 5	ŷ	$\Diamond$	
Person 6	ŷ		$\Diamond$
Person 7	ŷ	$\Diamond$	
Person 8	<b>◇</b>		



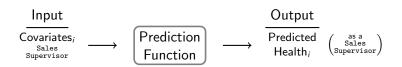
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø		
Person 2	Ø		
Person 3	ŷ	0	
Person 4	ŷ		0
Person 5	ŷ	$\Diamond$	
Person 6	ŷ		$\Diamond$
Person 7	ŷ	$\Diamond$	
Person 8	<b>◇</b>		



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	
Person 2	Ø	ŷ	
Person 3	ŷ	$\bigcirc$	
Person 4	ŷ	ŷ	0
Person 5	ŷ	<b></b>	
Person 6	ŷ	ŷ	$\Diamond$
Person 7	ŷ	<b>\$</b>	
Person 8	<b>◇</b>	ŷ	



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	
Person 2	Ø	ŷ	
Person 3	ŷ	$\bigcirc$	
Person 4	ŷ	ŷ	0
Person 5	ŷ	<b>\$</b>	
Person 6	ŷ	ŷ	$\Diamond$
Person 7	ŷ	Ŷ	
Person 8	<b>◇</b>	ŷ	



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	
Person 2	$\bigcirc$	ŷ	
Person 3	ŷ	$\bigcirc$	
Person 4	ŷ	ŷ	0
Person 5	ŷ	<b></b>	
Person 6	ŷ	ŷ	$\Diamond$
Person 7	ŷ	<b>◇</b>	
Person 8	<b>◇</b>	ŷ	

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion



	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	ŷ
Person 2	Ø	ŷ	ŷ
Person 3	ŷ	$\bigcirc$	ŷ
Person 4	ŷ	ŷ	Ø
Person 5	ŷ	<b>\$</b>	ŷ
Person 6	ŷ	ŷ	<b>\$</b>
Person 7	ŷ	<b>\$</b>	ŷ
Person 8	<b></b>	ŷ	ŷ

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion

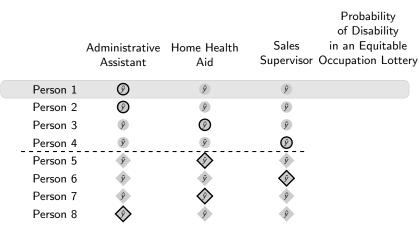


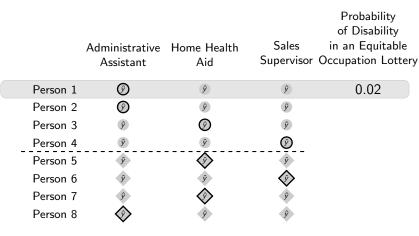
	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	ŷ
Person 2	Ø	ŷ	ŷ
Person 3	ŷ	$\bigcirc$	ŷ
Person 4	ŷ	ŷ	Ø
Person 5	ŷ	<b>\$</b>	ŷ
Person 6	ŷ	ŷ	<b>\$</b>
Person 7	ŷ	<b>\$</b>	ŷ
Person 8	<b>◇</b>	ŷ	ŷ

Robins 1986 Hahn 1998

	Administrative Assistant	Home Health Aid	Sales Supervisor
Person 1	Ø	ŷ	ŷ
Person 2	Ø	ŷ	ŷ
Person 3	ŷ	Ø	ŷ
Person 4	ŷ	ŷ	Ø
Person 5	ŷ	<b></b>	ŷ
Person 6	ŷ	ŷ	<b></b>
Person 7	ŷ	<b>②</b>	ŷ
Person 8	<b>◇</b>	ŷ	ŷ

	Administrative Assistant	Home Health Aid	Sales Supervisor	
Person 1	Ø	ŷ	ŷ	
Person 2	Ø	ŷ	ŷ	
Person 3	ŷ	Ø	ŷ	
Person 4	ŷ	ŷ	Ø	
Person 5	ŷ	<b></b>	ŷ	
Person 6	ŷ	ŷ	<b>\$</b>	
Person 7	ŷ	<b>②</b>	ŷ	
Person 8	<b>♦</b>	ŷ	ŷ	





	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	$\bigcirc$	ŷ	
Person 4	ŷ	ŷ	Ø	
Person 5	ŷ	Ø	ŷ	
Person 6	ŷ	ŷ	Ŷ	
Person 7	ŷ	<b>\$</b>	ŷ	
Person 8	<b>♦</b>	ŷ	ŷ	

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lotter
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	
Person 5	ŷ	Ø	ŷ	
Person 6	ŷ	ŷ	<b>\$</b>	
Person 7	ŷ	<b>\$</b>	ŷ	
Person 8	<b>♦</b>	ŷ	ŷ	

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<b></b>	ŷ	
Person 6	ŷ	ŷ	<b>\$</b>	
Person 7	ŷ	<b>\$</b>	ŷ	
Person 8	<b>♦</b>	ŷ	ŷ	

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lotter
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<del>-</del>	ŷ	0.02
Person 6	ŷ	ŷ	<b>\$</b>	
Person 7	ŷ	<b>\$</b>	ŷ	
Person 8	<b>♦</b>	ŷ	ŷ	

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>\$</b>	0.03
Person 7	ŷ	<b>\$</b>	ŷ	
Person 8	<b>\$</b>	ŷ	ŷ	

Ian Lundberg Introduction Data Causal Question Estimation

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>\$</b>	0.03
Person 7	ŷ	<b></b>	ŷ	0.04
Person 8	<b>◇</b>	ŷ	ŷ	

Ian Lundberg Introduction Data Causal Question Estimation

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	<b>Ø</b>	$\hat{y}$	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	$\bigcirc$	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>⋄</b>	0.03
Person 7	ŷ	<b>\$</b>	ŷ	0.04
Person 8	<b>\$</b>	ŷ	ŷ	0.03

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	$\hat{y}$	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	0.03
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	Ŷ	0.03
Person 7	ŷ	<b>\$</b>	ŷ	0.04
Person 8	<b>◇</b>	ŷ	ŷ	0.03

lan Lundberg Introduction Data Causal Question

	Administrative Assistant	Home Health Aid	C	Probability of Disability an Equitable upation Lottery
Person 1	Ø	ŷ	ŷ	0.02
Person 2	Ø	ŷ	ŷ	0.01
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	<b>②</b>	0.03
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>�</b>	0.03
Person 7	ŷ	<b>\$</b>	ŷ	0.04
Person 8	<b>♦</b>	ŷ	ŷ	0.03

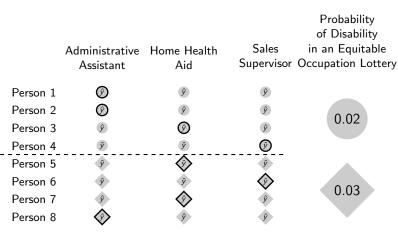
lan Lundberg Introduction Data Ca

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	
Person 2	Ø	ŷ	ŷ	0.02
Person 3	ŷ	$\bigcirc$	ŷ	0.02
Person 4	ŷ	ŷ	Ø	
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>\$</b>	0.03
Person 7	ŷ	<b>②</b>	ŷ	0.04
Person 8	<b>♦</b>	ŷ	ŷ	0.03

Discussion

	Administrative Assistant	Home Health Aid	Sales Supervisor	Probability of Disability in an Equitable Occupation Lottery
Person 1	Ø	ŷ	ŷ	
Person 2	Ø	ŷ	ŷ	0.00
Person 3	ŷ	Ø	ŷ	0.02
Person 4	ŷ	ŷ	Ø	
Person 5	ŷ	<b></b>	ŷ	0.02
Person 6	ŷ	ŷ	<b>\$</b>	0.03
Person 7	ŷ	<b>\$</b>	ŷ	0.04
Person 8	<b>②</b>	ŷ	ŷ	0.03
	•			

Discussion



- 1) Learn a prediction function
- 2) Predict counterfactuals
- 3) Aggregate to an estimate

					Probability of Disability
		Administrative	Home Health	Sales	in an Equitable
		Assistant	Aid	Supervisor	Occupation Lottery
	Person 1	Ø	ŷ	ŷ	
	Person 2	Ø	ŷ	ŷ	0.00
	Person 3	ŷ	Ø	ŷ	0.02
	Person 4	ŷ	ŷ	Ø	
•	Person 5	ŷ	<b></b>	ŷ	
	Person 6	ŷ	ŷ	Ŷ	0.02
	Person 7	ŷ	<b>\$</b>	ŷ	0.03
	Person 8	<b>\$</b>	ŷ	ŷ	

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

#### Structure of the talk

Introduction Disparities call for explanations

Data Current Population Survey

Causal Question How an intervention would close a gap

→ Estimation Causal assumptions and predictive tools

Results Partially closing a gap in health

Broadening out A framework for quantitative methodology

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

### Structure of the talk

Introduction Disparities call for explanations

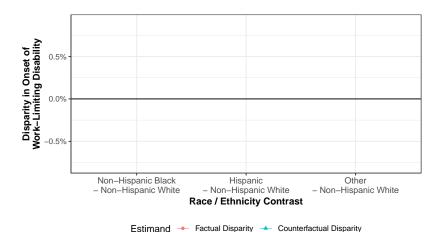
Data Current Population Survey

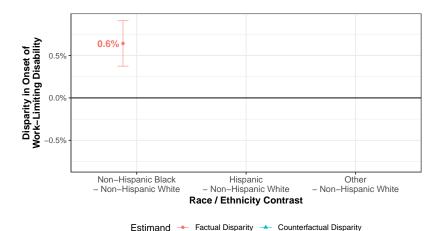
Causal Question How an intervention would close a gap

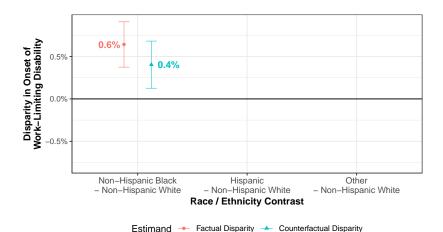
Estimation Causal assumptions and predictive tools

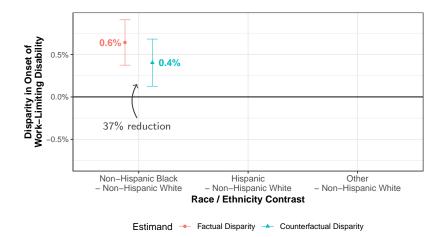
→ Results Partially closing a gap in health

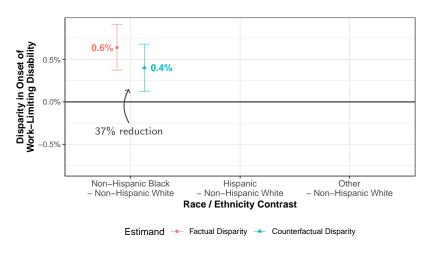
Broadening out A framework for quantitative methodology

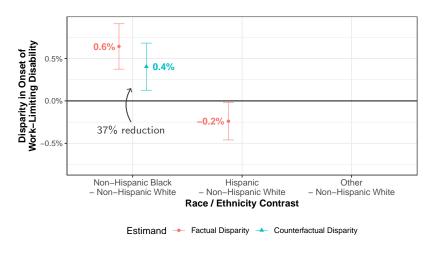


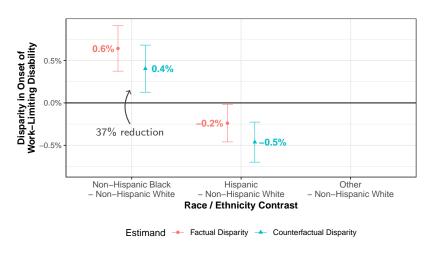


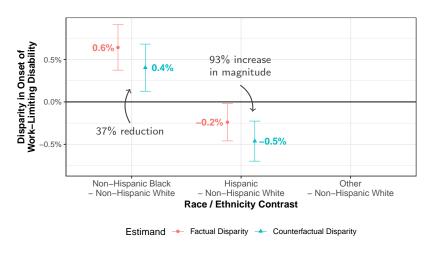


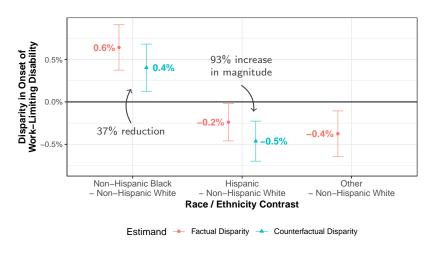


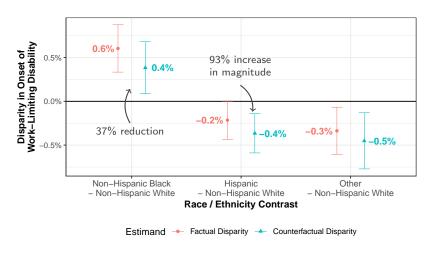


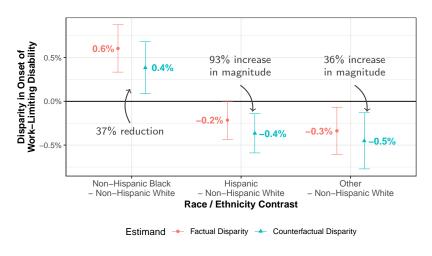












#### **Standard Regression**

$$Y=eta_0+eta_1 imes exttt{Black} \ +eta_2 imes exttt{College} \ +eta_3 imes exttt{Lagged Health} \ +eta_4 imes exttt{Occupation} \ +eta( exttt{other covariates}) \ +\epsilon$$

#### **Standard Regression**

$$Y = eta_0 + egin{pmatrix} eta_1 imes exttt{Black} \\ &+ eta_2 imes exttt{College} \\ &+ eta_3 imes exttt{Lagged Health} \\ &+ eta_4 imes exttt{Occupation} \\ &+ \left( exttt{other covariates} 
ight) \\ &+ \epsilon \end{pmatrix}$$

$$Y = eta_0 + \left(eta_1 imes exttt{Black}
ight) + eta_2 imes exttt{College} + eta_3 imes exttt{Lagged Health} + eta_4 imes exttt{Occupation} + \left( exttt{other covariates}
ight) + \epsilon$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned Health if Occupations were Equitably Assigned

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}} \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + \left( exttt{other covariates} 
ight) \ + \epsilon$$

1

Statistically holds everything equal

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned Health if Occupations were Equitably Assigned

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}} \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + \left( exttt{other covariates} 
ight) \ + \epsilon$$

Statistically holds
everything
equal

### **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned Health if Occupations were Equitably Assigned

1

An intervention to equalize occupation

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = \beta_0 + \beta_1 \times \text{Black}$$
  
  $+ \beta_2 \times \text{College}$   
  $+ \beta_3 \times \text{Lagged Health}$   
  $+ \beta_4 \times \text{Occupation}$   
  $+ (\text{other covariates})$   
  $+ \epsilon$ 

### **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Standard Regression

**Gap-Closing Estimand** 

Ian Lundberg

$$Y = eta_0 + \left(eta_1 imes exttt{Black}
ight) \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + \left( ext{other covariates}
ight) \ + \epsilon$$

# **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if
Occupations
were Equitably
Assigned

Health if
Occupations
were Equitably
Assigned

**Standard Regression** 

**Gap-Closing Estimand** 

Substantive Meaning

Ian Lundberg

$$Y = eta_0 + \overbrace{eta_1 imes ext{Black}} + eta_2 imes ext{College} + eta_3 imes ext{Lagged Health} + eta_4 imes ext{Occupation} + ( ext{other covariates}) + \epsilon$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if
Occupations
were Equitably
Assigned

Health if
Occupations
were Equitably
Assigned

Standard Regression

**Gap-Closing Estimand** 

Substantive Meaning Differences within subgroups

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}} \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + exttt{(other covariates)}$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

#### **Standard Regression**

Substantive Meaning

 $+\epsilon$ 

Differences within subgroups

#### **Gap-Closing Estimand**

Outcome of an intervention

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes \mathtt{Black}} + eta_2 imes \mathtt{College} + eta_3 imes \mathtt{Lagged Health} + eta_4 imes \mathtt{Occupation} + eta_4 imes \mathtt{other covariates} + \epsilon$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if
Occupations
were Equitably
Assigned

Health if Occupations were Equitably Assigned

#### **Standard Regression**

Substantive Meaning

Choice of Covariates

Differences within subgroups

#### **Gap-Closing Estimand**

Outcome of an intervention

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = \beta_0 + \beta_1 \times \text{Black}$$
  
  $+ \beta_2 \times \text{College}$   
  $+ \beta_3 \times \text{Lagged Health}$   
  $+ \beta_4 \times \text{Occupation}$   
  $+ (\text{other covariates})$   
  $+ \epsilon$ 

# **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if
Occupations
were Equitably
Assigned

Health if Occupations were Equitably Assigned

#### **Standard Regression**

Substantive Meaning Differences within subgroups

Choice of Covariates

.

#### **Gap-Closing Estimand**

Outcome of an intervention

lan Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}} \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + eta_6 imes exttt{Cother covariates}$$

# **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

#### Standard Regression

Substantive Meaning

 $+\epsilon$ 

Differences within subgroups

Choice of Covariates

.

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + egin{pmatrix} eta_1 imes exttt{Black} \\ + eta_2 imes exttt{College} \\ + eta_3 imes exttt{Lagged Health} \\ + eta_4 imes exttt{Occupation} \\ + egin{pmatrix} exttt{other covariates} \end{pmatrix}$$

# **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

### Standard Regression

Substantive Meaning

 $+\epsilon$ 

Differences within subgroups

Choice of Covariates

?

Machine learning !

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes ext{Black}} + eta_2 imes ext{College} + eta_3 imes ext{Lagged Health} + eta_4 imes ext{Occupation} + ( ext{other covariates}) + \epsilon$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if
Occupations
were Equitably
Assigned

Health if Occupations were Equitably Assigned

#### Standard Regression

Substantive Meaning	Differences within subgroups
Choice of Covariates	?
Machine learning	?

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \left(eta_1 imes exttt{Black}
ight) \ + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + \left( ext{other covariates}
ight) \ + \epsilon$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

Standard	Regression

Substantive Meaning	Differences within subgroups
Choice of Covariates	?
Machine learning	?

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Plug in and go!

Results

$$Y = \beta_0 + \beta_1 \times \text{Black}$$
  
  $+ \beta_2 \times \text{College}$   
  $+ \beta_3 \times \text{Lagged Health}$   
  $+ \beta_4 \times \text{Occupation}$   
  $+ (\text{other covariates})$   
  $+ \epsilon$ 

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

Charadanal	D
Standard	Regression

Substantive Meaning	Differences within subgroups
Choice of Covariates	?
Machine learning	?

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Plug in and go!

lan Lundberg

Policy Relevance

Introduction

Data

Causal Question

Estimation

Results

$$Y = \beta_0 + \beta_1 \times \text{Black}$$
  
  $+ \beta_2 \times \text{College}$   
  $+ \beta_3 \times \text{Lagged Health}$   
  $+ \beta_4 \times \text{Occupation}$   
  $+ (\text{other covariates})$   
  $+ \epsilon$ 

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

Discussion

Standard	Regression

Substantive Meaning	Differences within subgroups
Choice of Covariates	?
Machine learning	?
Policy Relevance	?

#### **Gap-Closing Estimand**

Outcome of an intervention

Those needed to identify the effect of occupation

Plug in and go!

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}}^{ exttt{Flack}} + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + exttt{(other covariates)} \ + \epsilon$$

### **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

	Standard Regression	Gap-Closing Estimand
Substantive Meaning	Differences within subgroups	Outcome of an intervention
Choice of Covariates	?	Those needed to identify the effect of occupation
Machine learning	?	Plug in and go!
Policy Relevance	?	Speaks to the initial response to policy

Ian Lundberg

Introduction

Data

Causal Question

Estimation

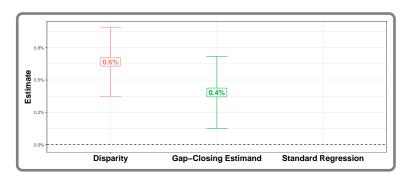
Results

$$Y=eta_0 + egin{pmatrix} eta_1 imes exttt{Black} \ +eta_2 imes exttt{College} \ +eta_3 imes exttt{Lagged Health} \ +eta_4 imes exttt{Occupation} \ +\left( exttt{other covariates}
ight) \ +\epsilon \end{pmatrix}$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned Health if Occupations were Equitably Assigned



Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

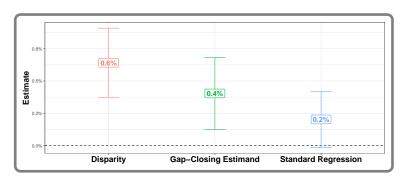
$$Y=eta_0+egin{array}{c} +eta_1 imes exttt{Black} \ +eta_2 imes exttt{College} \ +eta_3 imes exttt{Lagged Health} \ +eta_4 imes exttt{Occupation} \ +\left( exttt{other covariates}
ight) \ +\epsilon \end{array}$$

## **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white



Health if Occupations were Equitably Assigned



Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

$$Y = eta_0 + \overbrace{eta_1 imes exttt{Black}}^{ exttt{Flack}} + eta_2 imes exttt{College} \ + eta_3 imes exttt{Lagged Health} \ + eta_4 imes exttt{Occupation} \ + exttt{(other covariates)} \ + \epsilon$$

### **Gap-Closing Estimand**

Non-Hispanic Black Non-Hispanic white

Health if Occupations were Equitably Assigned

	Standard Regression	Gap-Closing Estimand
Substantive Meaning	Differences within subgroups	Outcome of an intervention
Choice of Covariates	?	Those needed to identify the effect of occupation
Machine learning	?	Plug in and go!
Policy Relevance	?	Speaks to the initial response to policy

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Place race in a causal framework with real people

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

### Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Produce evidence to inform local policy interventions

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Produce evidence to inform local policy interventions

Contrast: Structural claims (e.g. eliminate dangerous jobs)

are empirically intractable

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Produce evidence to inform local policy interventions

Contrast: Structural claims (e.g. eliminate dangerous jobs)

are empirically intractable

Discover treatment assignment rules that close disparities

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Produce evidence to inform local policy interventions

Contrast: Structural claims (e.g. eliminate dangerous jobs)

are empirically intractable

Discover treatment assignment rules that close disparities

Contrast: Precision medicine searches for effective

person-specific treatments

Place race in a causal framework with real people

Contrast: Audit studies place race in a causal framework

but with fictitious people

Contrast: Disparities involve real people

but without a causal framework

Produce evidence to inform local policy interventions

Contrast: Structural claims (e.g. eliminate dangerous jobs)

are empirically intractable

Discover treatment assignment rules that close disparities

Contrast: Precision medicine searches for effective

person-specific treatments

The treatments that are effective to close population disparities might be different

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

### **Structure of the talk**

Introduction
Causal Question

Estimation

→ Results

Broadening out

Approaches to understand disparities

How an intervention would close a gap

Causal assumptions and predictive tools

Partially closing a gap in health

A framework for quantitative methodology

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

General method The gap-closing estimand:

The disparity across social categories that would persist if we equalized a treatment

Specific example

Occupational segregation contributes to racial disparities in health

### Structure of the talk

Introduction
Causal Question

Estimation

Results

→ Broadening out

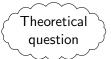
Approaches to understand disparities

How an intervention would close a gap Causal assumptions and predictive tools

Partially closing a gap in health

A framework for quantitative methodology

Ian Lundberg







What actually happens:



What actually happens:

Familiar methods (regression)



### What actually happens:





lan Lundberg Introduction Data Causal Question Estimation Results Discussion

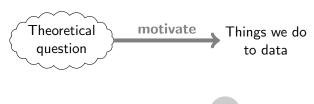


Lundberg, Johnson, Stewart

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review

lan Lundberg Introduction Data Causal Question Estimation Results Discussion





Discussion

Results

Lundberg, Johnson, Stewart
What is Your Estimand?
Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review

lan Lundberg Introduction Data Causal Question Estimation





A unit-specific quantity

Lundberg, Johnson, Stewart

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review

Ian Lundberg





A unit-specific quantity

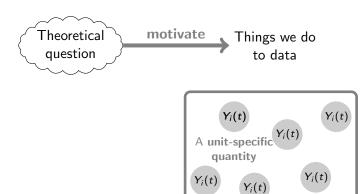
Discussion

Lundberg, Johnson, Stewart

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review

lan Lundberg Introduction Data Causal Question Estimation Results



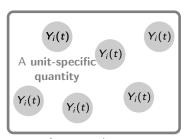
Aggregated over a target population

Lundberg, Johnson, Stewart What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory Forthcoming, *American Sociological Review* 

lan Lundberg Introduction Data Causal Question Estimation Results Discussion





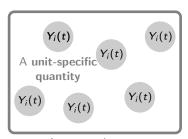
Aggregated over a target population

Lundberg, Johnson, Stewart What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory Forthcoming, *American Sociological Review* 



Our framework expands <u>theory</u>, links to transparent <u>evidence</u>, and unlocks computational <u>tools</u>

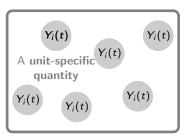


Aggregated over a target population

Lundberg, Johnson, Stewart What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory Forthcoming, *American Sociological Review* 



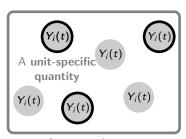


Aggregated over a target population

Lundberg, Johnson, Stewart What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory Forthcoming, American Sociological Review



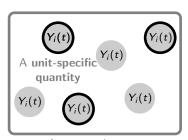


Aggregated over a target population

Lundberg, Johnson, Stewart What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory Forthcoming, *American Sociological Review* 





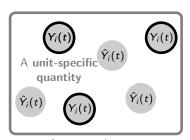
Aggregated over a target population

Lundberg, Johnson, Stewart

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review





Aggregated over a target population

Lundberg, Johnson, Stewart

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory
Forthcoming, American Sociological Review

Ian Lundberg

## Ian Lundberg ianlundberg.org

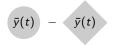
The gap-closing estimand

Categories

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



Treatment



**Counterfactual Disparity** 

Ian Lundberg

Introduction

Data

Causal Question

Estimation

Results

Discussion