Prediction in Social Science

A Tool to Study Inequality in Populations

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Replication code is available in links on my CV at ianlundberg.org. Research reported in this talk was supported by The Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health under Award Number P2CHD047879, and by the Russell Sage Foundation.

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Three possible uses:

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Three possible uses:

1) Prediction for individuals

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Three possible uses:

1) Prediction for individuals — very hard

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Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description

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Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description — useful

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Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description — useful
3) Prediction for causal claims

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Three possible uses:

1)	Prediction for individuals	very hard
2)	Prediction for description	useful
3)	Prediction for causal claims	opportunities abound

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Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description — useful
3) Prediction for causal claims — opportunities abound
   - — Define the intervention
   - — Causal assumptions
   - — Estimation
   - — Empirical examples

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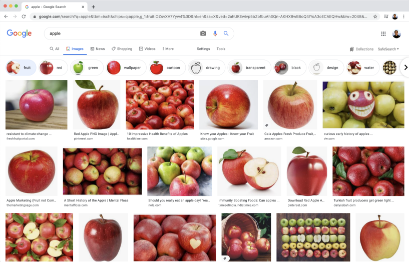
Standard prediction setting

Standard prediction setting

$\longrightarrow$ Apple

Standard prediction setting

→ Apple



Standard prediction setting

 $\longrightarrow$ Apple

Social settings

Social Data $\xrightarrow{?}$ Social Outcome


The New York Times Magazine
PLAY THE CROSSWORD
Account
FEATURE
Can an Algorithm Tell When Kids Are in Danger?
Child protective agencies are haunted when they fail to save kids. Pittsburgh officials believe a new data analysis program is helping them make better judgment calls.

Bernard Parker, left, was rated high risk; Dylan Fugett was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias

There's software used across the country to predict future criminals.
And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

Standard prediction setting

$\longrightarrow$ Apple

Social settings

Social Data $\xrightarrow{?}$ Social Outcome

Measuring the predictability of life outcomes with a scientific mass collaboration

Matthew J. Salganik[a,1], Ian Lundberg[a], Alexander T. Kindel[a], Caitlin E. Ahearn[b], Khaled Al-Ghoneim[c], Abdullah Almaatouq[d,e], Drew M. Altschul[f], Jennie E. Brand[b,g], Nicole Bohme Carnegie[h], Ryan James Compton[i], Debanjan Datta[j], Thomas Davidson[k], Anna Filippova[l], Connor Gilroy[m], Brian J. Goode[n], Eaman Jahani[o], Ridhi Kashyap[p,q,r], Antje Kirchner[s], Stephen McKay[t], Allison C. Morgan[u], Alex Pentland[e], Kivan Polimis[v], Louis Raes[w], Daniel E. Rigobon[x], Claudia V. Roberts[y], Diana M. Stanescu[z], Yoshihiko Suhara[e], Adaner Usmani[aa], Erik H. Wang[z], Muna Adem[bb], Abdulla Alhajri[cc], Bedoor AlShebli[dd], Redwane Amin[ee], Ryan B. Amos[y], Lisa P. Argyle[ff], Livia Baer-Bositis[gg], Moritz Büchi[hh], Bo-Ryehn Chung[ii], William Eggert[jj], Gregory Faletto[kk], Zhilin Fan[ll], Jeremy Freese[gg], Tejomay Gadgil[mm], Josh Gagné[gg], Yue Gao[nn], Andrew Halpern-Manners[bb], Sonia P. Hashim[y], Sonia Hausen[gg], Guanhua He[oo], Kimberly Higuera[gg], Bernie Hogan[pp], Ilana M. Horwitz[qq], Lisa M. Hummel[gg], Naman Jain[x], Kun Jin[rr], David Jurgens[ss], Patrick Kaminski[bb,tt], Areg Karapetyan[uu,vv], E. H. Kim[gg], Ben Leizman[y], Naijia Liu[z], Malte Möser[y], Andrew E. Mack[z], Mayank Mahajan[y], Noah Mandell[ww], Helge Marahrens[bb], Diana Mercado-Garcia[qq], Viola Mocz[xx], Katariina Mueller-Gastell[gg], Ahmed Musse[yy], Qiankun Niu[ee], William Nowak[zz], Hamidreza Omidvar[aaa], Andrew Or[y], Karen Ouyang[y], Katy M. Pinto[bbb], Ethan Porter[ccc], Kristin E. Porter[ddd], Crystal Qian[y], Tamkinat Rauf[gg], Anahit Sargsyan[eee], Thomas Schaffner[y], Landon Schnabel[gg], Bryan Schonfeld[z], Ben Sender[fff], Jonathan D. Tang[y], Emma Tsurkov[gg], Austin van Loon[gg], Onur Varol[ggg,hhh], Xiafei Wang[iii], Zhi Wang[hhh,jjj], Julia Wang[y], Flora Wang[fff], Samantha Weissman[y], Kirstie Whitaker[kkk,lll], Maria K. Wolters[mmm], Wei Lee Woon[nnn], James Wu[ooo], Catherine Wu[y], Kengran Yang[aaa], Jingwen Yin[ll], Bingyu Zhao[ppp], Chenyun Zhu[ll], Jeanne Brooks-Gunn[qqq,rrr], Barbara E. Engelhardt[y,ii], Moritz Hardt[sss], Dean Knox[z], Karen Levy[ttt], Arvind Narayanan[y], Brandon M. Stewart[a], Duncan J. Watts[uuu,vvv,www], and Sara McLanahan[a,1]

Fragile Families

& Child Wellbeing Study

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& Child Wellbeing Study
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Predictor variables | **Outcomes**

Cases

→ Apple

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Predictor variables (12,942)

Outcomes

Cases (4,242)

Childhood Experiences
Birth to age 9

→

Apple

Fragile Families
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Predictor variables (12,942)

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Outcomes

GPA
Age 15

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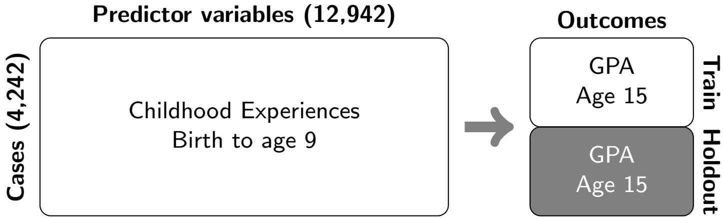

Fragile Families
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Mass collaboration
160 teams attempted this task

Predictor variables (12,942)

Cases (4,242)

Childhood Experiences
Birth to age 9

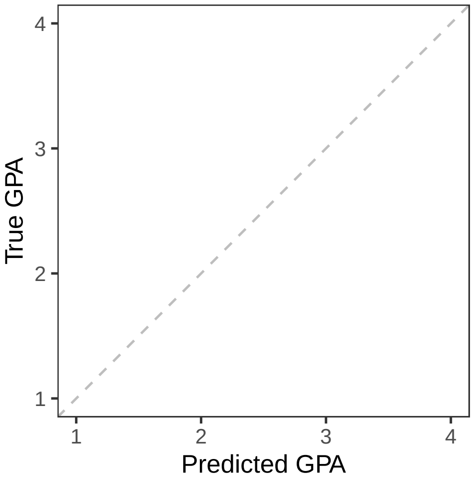
→

Outcomes

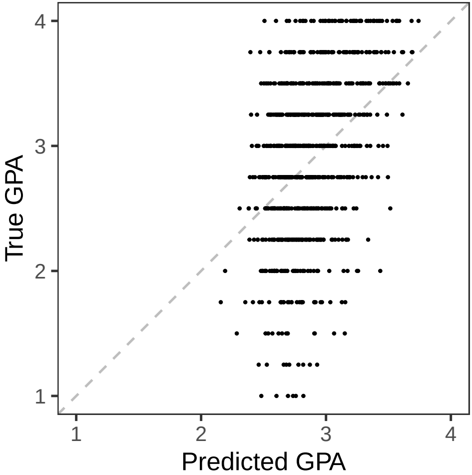
GPA
Age 15
Train

GPA
Age 15
Holdout

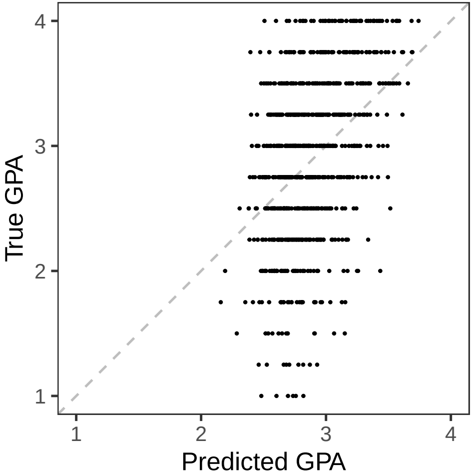
The best of 160 submissions



The best of 160 submissions

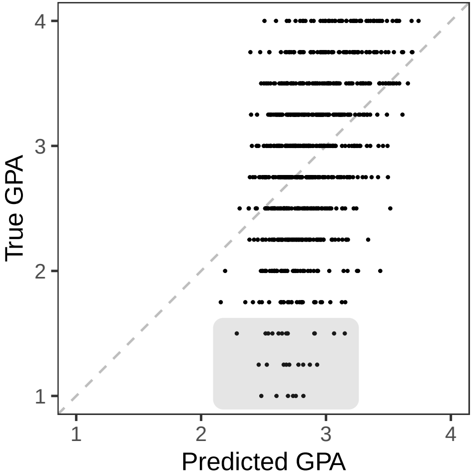


The best of 160 submissions



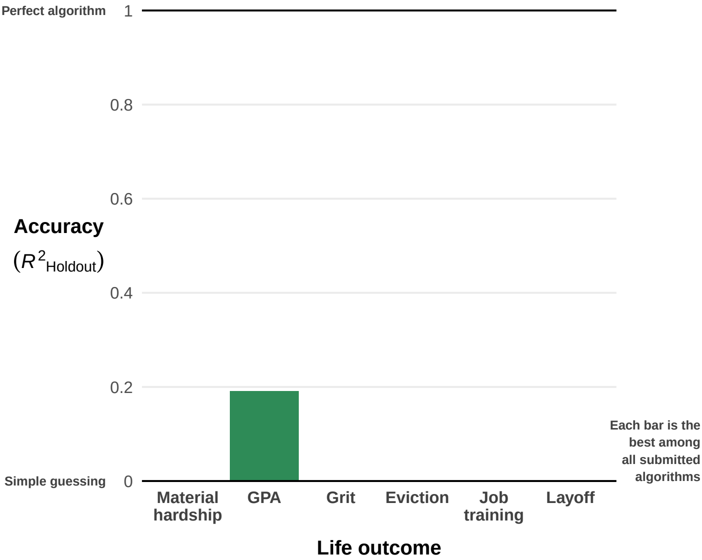
At any predicted GPA, the true GPA varies tremendously

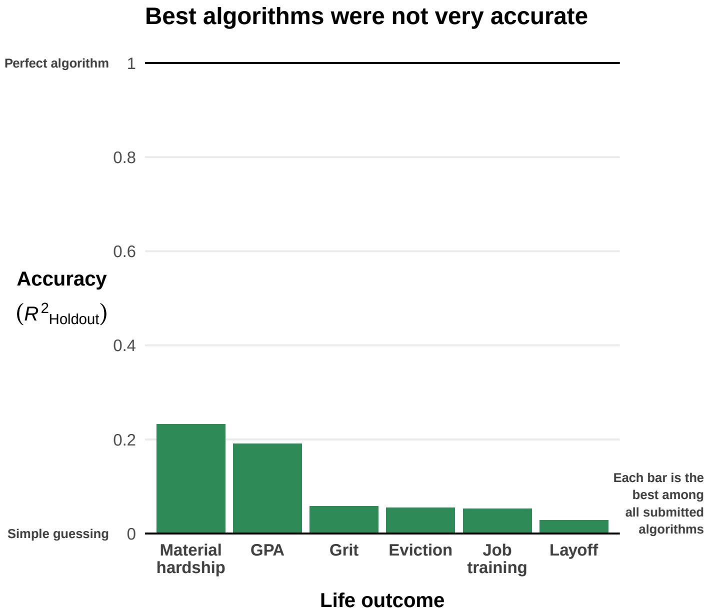
The best of 160 submissions



At any predicted GPA, the true GPA varies tremendously

Best algorithms were not very accurate




Best algorithms were not very accurate
Perfect algorithm
1
0.8
0.6
Accuracy
(R^2_{Holdout})
0.4
0.2
Simple guessing
0
Each bar is the best among all submitted algorithms
Material hardship
GPA
Grit
Eviction
Job training
Layoff
Life outcome

Machine learning was

really bad

at predicting individual outcomes in this social setting

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$\longrightarrow$ Apple

Machine learning was
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$\xrightarrow{\text{very hard}}$ Evicted

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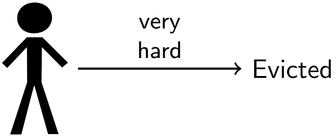

$$\text{MSE}\left(Y, \hat{Y}\right) = \text{E}\left(\text{V}(Y \mid \vec{X})\right) + \text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)$$

Mean squared prediction error	Outcome variance given signal	MSE for the conditional mean

Machine learning was
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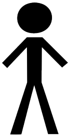

$\xrightarrow{\text{very hard}}$ Evicted

$$\underbrace{\boxed{\text{MSE}\left(Y, \hat{Y}\right)}}_{\text{Mean squared prediction error}} = \underbrace{\text{E}\left(\text{V}(Y \mid \vec{X})\right)}_{\text{Outcome variance given signal}} + \underbrace{\text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)}_{\text{MSE for the conditional mean}}$$

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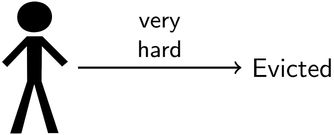

$$\underbrace{\text{MSE}\left(Y, \hat{Y}\right)}_{\substack{\text{Mean squared} \\ \text{prediction error}}} = \underbrace{\text{E}\left(\text{V}(Y \mid \vec{X})\right)}_{\substack{\text{Outcome variance} \\ \text{given signal}}} + \underbrace{\text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)}_{\substack{\text{MSE for the} \\ \text{conditional mean}}}$$

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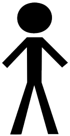

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$\uparrow$

Potentially large in social settings

Machine learning was
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$\xrightarrow{\text{very hard}}$ Evicted

$$\underbrace{\mathrm{MSE}\left(Y, \hat{Y}\right)}_{\substack{\text{Mean squared}\\ \text{prediction error}}} = \underbrace{\mathrm{E}\left(\mathrm{V}(Y \mid \vec{X})\right)}_{\substack{\text{Outcome variance}\\ \text{given signal}}} + \boxed{\underbrace{\mathrm{MSE}\left(\hat{Y}, \mathrm{E}(Y \mid \vec{X})\right)}_{\substack{\text{MSE for the}\\ \text{conditional mean}}}}$$

↑

Potentially large in
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$$\text{MSE}\left(Y, \hat{Y}\right) = \text{E}\left(\text{V}(Y \mid \vec{X})\right) + \text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)$$

Mean squared prediction error

Outcome variance given signal

↑ Potentially large in social settings

MSE for the conditional mean

↑ Progress still possible for questions about conditional means

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$$\text{MSE}\left(Y, \hat{Y}\right) = \text{E}\left(\text{V}(Y \mid \vec{X})\right) + \text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)$$

Mean squared prediction error

Outcome variance given signal

↑

Potentially large in social settings

MSE for the conditional mean

↑

Progress still possible for questions about conditional means

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1 in 4
is evicted

$$\text{MSE}\left(Y, \hat{Y}\right) = \text{E}\left(\text{V}(Y \mid \vec{X})\right) + \text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right)$$

Mean squared prediction error	Outcome variance given signal	MSE for the conditional mean
	Potentially large in social settings	Progress still possible for questions about conditional means

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Three possible uses:

→ 1) Prediction for individuals — very hard

2) Prediction for description — useful

3) Prediction for causal claims — opportunities abound

— Define the intervention
— Causal assumptions
— Estimation
— Empirical examples

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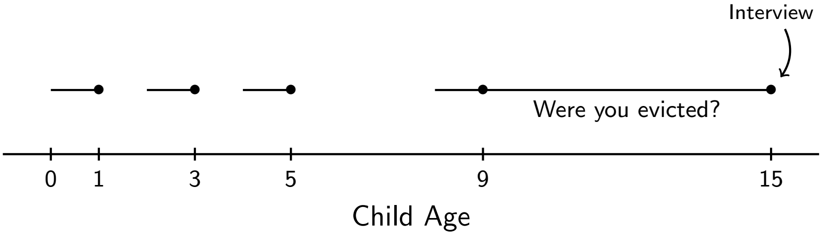
Demography (2019) 56:391–404
https://doi.org/10.1007/s13524-018-0735-y

CrossMark

A Research Note on the Prevalence of Housing Eviction Among Children Born in U.S. Cities

Ian Lundberg[1] · Louis Donnelly[2]


Interview
Were you evicted?
0
1
3
5
9
15
Child Age


Interview
Were you evicted?
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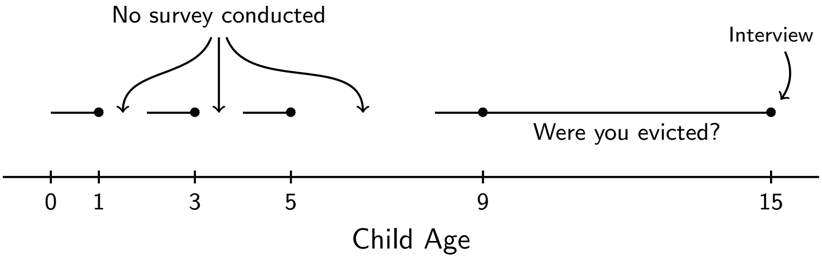
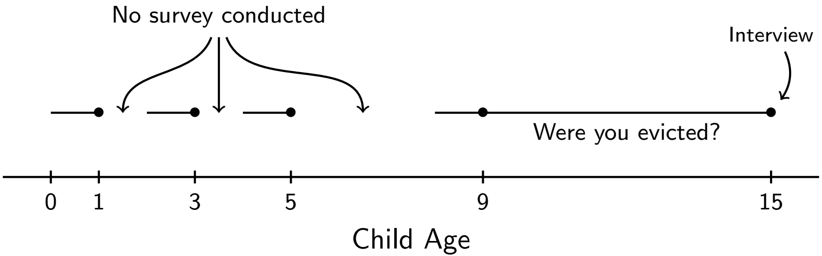
Child Age


No survey conducted
Interview
Were you evicted?
0
1
3
5
9
15
Child Age

Observed Data

	Ever Evicted?
Person 1	1
Person 2	?
Person 3	?
⋮	⋮
Average	?

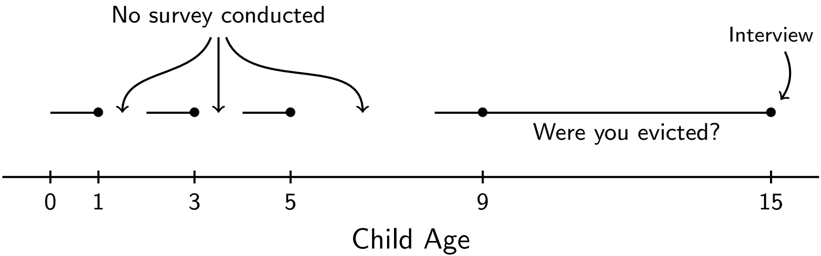


Observed Data

	Ever Evicted?
Person 1	1
Person 2	?
Person 3	?
⋮	⋮
Average	?

Lower Bound

	Ever Evicted?
Person 1	1
Person 2	0
Person 3	0
⋮	⋮
Average	8%



Observed Data

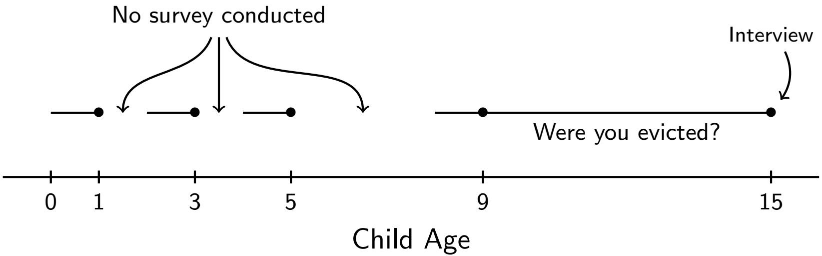
	Ever Evicted?
Person 1	1
Person 2	?
Person 3	?
⋮	⋮
Average	?

Lower Bound

	Ever Evicted?
Person 1	1
Person 2	0
Person 3	0
⋮	⋮
Average	8%

Predicted Data

	Ever Evicted?
Person 1	$\hat{Y}_1$
Person 2	$\hat{Y}_2$
Person 3	$\hat{Y}_3$
⋮	⋮



Observed Data

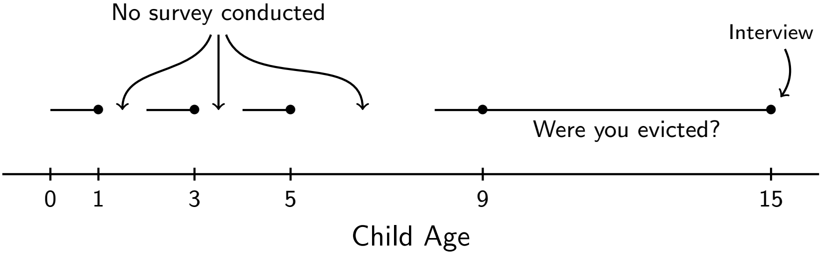
	Ever Evicted?
Person 1	1
Person 2	?
Person 3	?
⋮	⋮
Average	?

Lower Bound

	Ever Evicted?
Person 1	1
Person 2	0
Person 3	0
⋮	⋮
Average	8%

Predicted Data

	Ever Evicted?
Person 1	$\hat{Y}_1$
Person 2	$\hat{Y}_2$
Person 3	$\hat{Y}_3$
⋮	⋮
Average	15%



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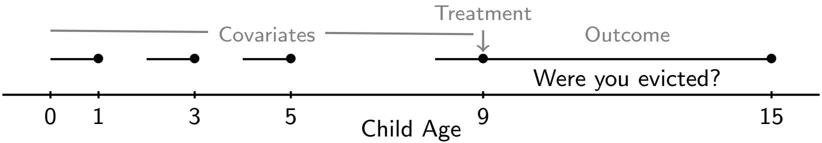
Government Assistance Protects Low-Income Families from Eviction

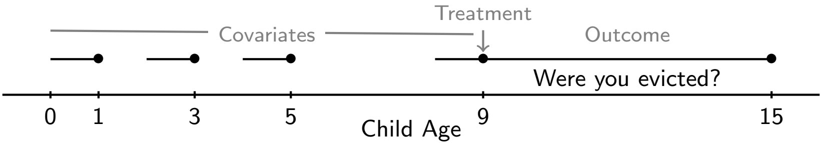
Ian Lundberg
Sarah L. Gold
Louis Donnelly
Jeanne Brooks-Gunn
Sara S. McLanahan

Journal of Policy Analysis and Management
2021

		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
Population	Person 1		
	Person 2		
	Person 3		



		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
Population	Person 1	$Y_1(1)$	$Y_1(0)$
	Person 2	$Y_2(1)$	$Y_2(0)$
	Person 3	$Y_3(1)$	$Y_3(0)$



		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
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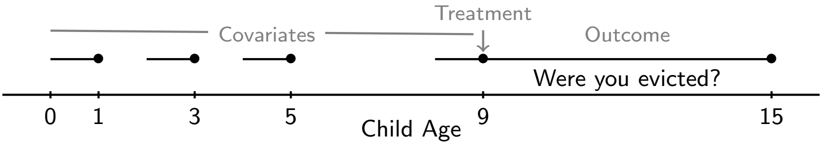
	Person 3	$Y_3(1)$	$Y_3(0)$



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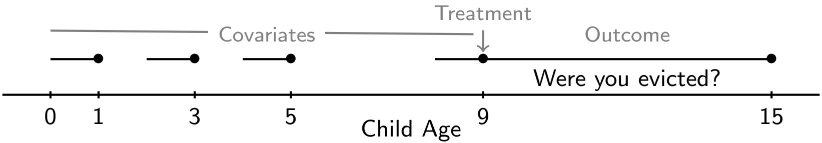
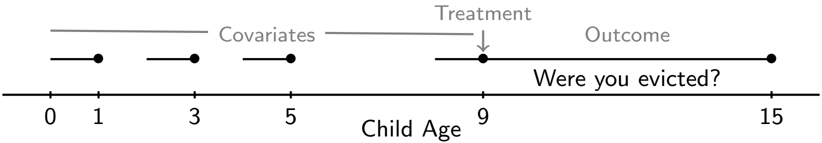
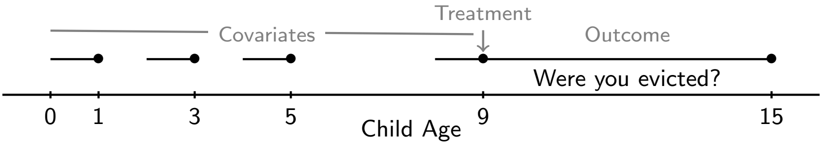


Treatment Condition

Population		1: Public Housing	0: No Rental Assistance
	Person 1	$Y_1(1)$	$Y_1(0)$
	Person 2	$Y_2(1)$	$Y_2(0)$
	Person 3	$Y_3(1)$	$Y_3(0)$

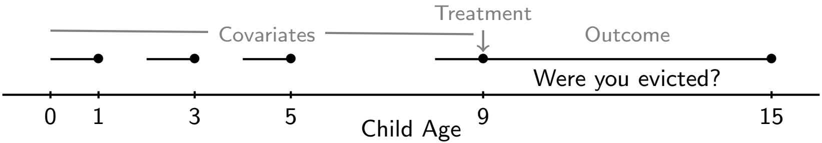


Population	Treatment Condition	
	1: Public Housing	0: No Rental Assistance
Person 1	?	$Y_1(0)$
Person 2	$Y_2(1)$	?
Person 3	?	$Y_3(0)$



Learn a prediction function

		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
Population	Person 1	?	$Y_1(0)$
	Person 2	$Y_2(1)$	?
	Person 3	?	$Y_3(0)$



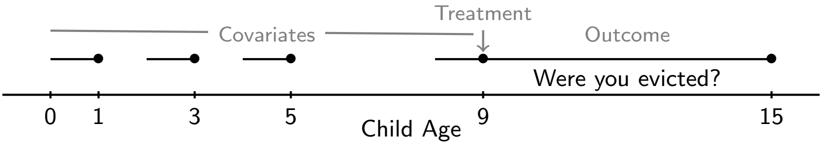
Learn a prediction function

		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
Population	Person 1	?	$Y_1(0)$
	Person 2	$Y_2(1)$	?
	Person 3	?	$Y_3(0)$

Predict the whole table

		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
Population	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$

Robins 1986
Hahn 1998



Learn a prediction function

Population		Treatment Condition	
		1: Public Housing	0: No Rental Assistance
	Person 1	?	$Y_1(0)$
	Person 2	$Y_2(1)$	?
	Person 3	?	$Y_3(0)$

Predict the whole table

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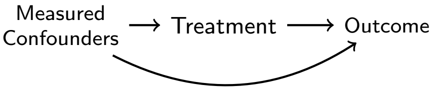

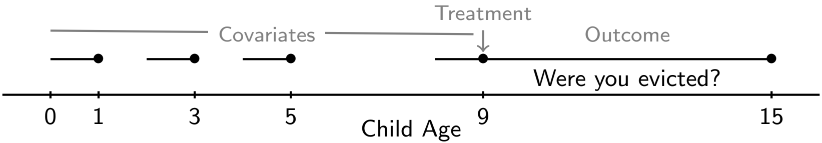

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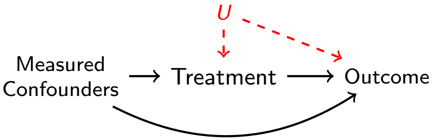

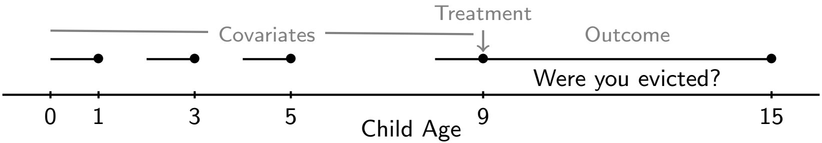

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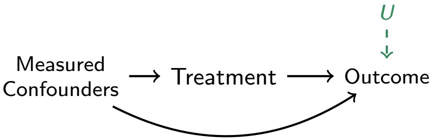

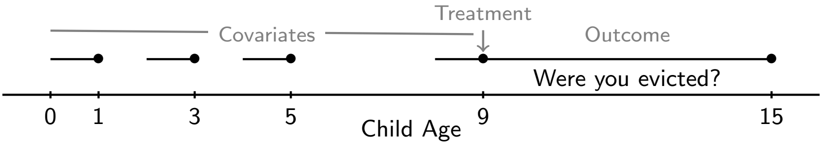

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Those factually in public housing

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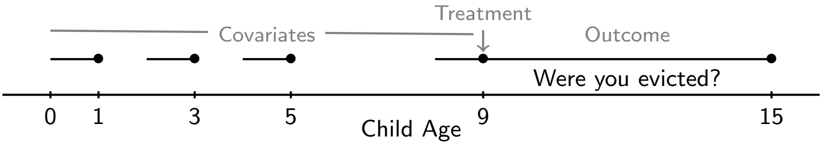
$$\begin{tikzcd} \text{Measured Confounders} \arrow[r] \arrow[rr, bend right] & \text{Treatment} \arrow[r] & \text{Outcome} \end{tikzcd}$$



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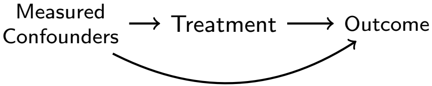
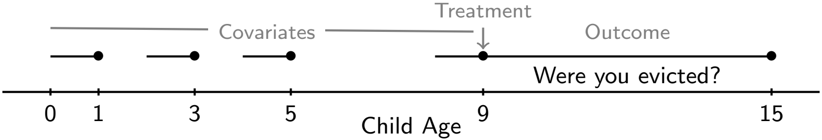
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
	Average	**3%**	

Those factually in public housing





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Those factually in public housing

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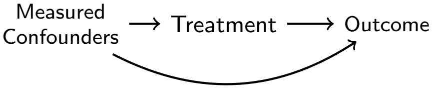
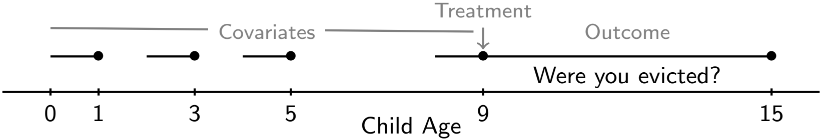
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
	Average	**3%**	**11%**





That was an old question
cast in a new way

(average treatment effect)
(as a prediction task)

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Translating to a prediction task also unlocks
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The **causal effect of race** is deeply fraught

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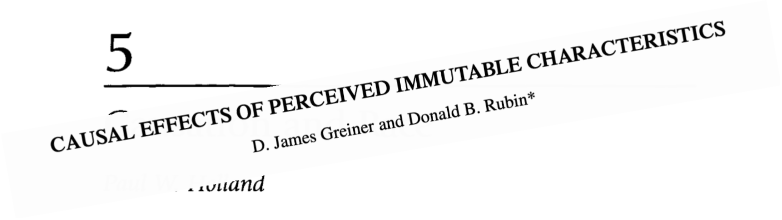
5

Causation and Race

Paul W. Holland

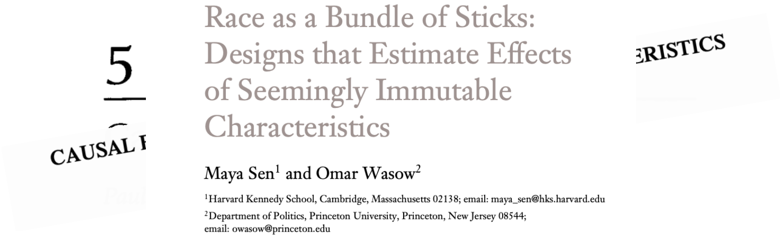
The **causal effect of race** is deeply fraught


5

CAUSAL EFFECTS OF PERCEIVED IMMUTABLE CHARACTERISTICS

D. James Greiner and Donald B. Rubin*

The **causal effect of race** is deeply fraught


Race as a Bundle of Sticks: Designs that Estimate Effects of Seemingly Immutable Characteristics

Maya Sen[1] and Omar Wasow[2]

[1]Harvard Kennedy School, Cambridge, Massachusetts 02138; email: maya_sen@hks.harvard.edu

[2]Department of Politics, Princeton University, Princeton, New Jersey 08544; email: owasow@princeton.edu

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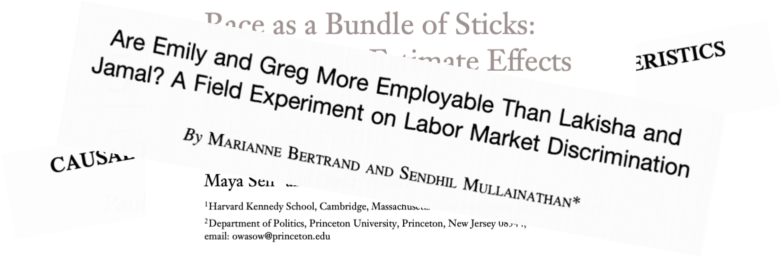

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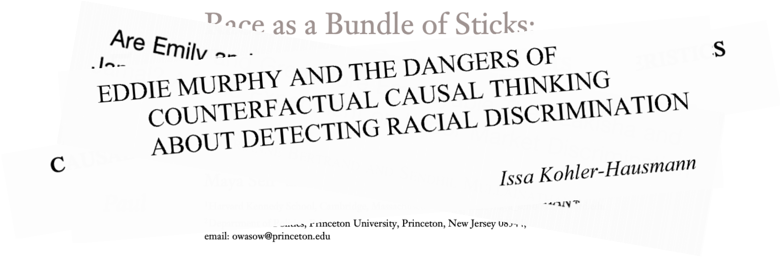

The **causal effect of race** is deeply fraught

Population		Treatment Condition	
		Black	White
	Person 1	Y_1(Black)	Y_1(White)
	Person 2	Y_2(Black)	Y_2(White)
	Person 3	Y_3(Black)	Y_3(White)
	Person 4	Y_4(Black)	Y_4(White)
	Person 5	Y_5(Black)	Y_5(White)
	Person 6	Y_6(Black)	Y_6(White)

The **causal effect of race** is deeply fraught

Black	Person 1
	Person 2
	Person 3
White	Person 4
	Person 5
	Person 6

Black	Person 1
	Person 2
	Person 3
White	Person 4
	Person 5
	Person 6

		As observed
Black	Person 1	Y_1
	Person 2	Y_2
	Person 3	Y_3
White	Person 4	Y_4
	Person 5	Y_5
	Person 6	Y_6

		As observed
Black	Person 1	Y_1
	Person 2	Y_2
	Person 3	Y_3
White	Person 4	Y_4
	Person 5	Y_5
	Person 6	Y_6

Descriptive Disparity

		As observed	Under intervention
Black	Person 1	Y_1	$Y_1(t)$
	Person 2	Y_2	$Y_2(t)$
	Person 3	Y_3	$Y_3(t)$
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		Descriptive Disparity	**Gap-Closing Estimand**

Can an intervention **close the gap**?

		As observed	Under intervention
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	Person 2	Y_2	$Y_2(t)$
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		Descriptive Disparity	**Gap-Closing Estimand**

Vanderweele & Robinson 2014

Jackson & Vanderweele 2018

Can an intervention **close the gap**?

		As observed	Under intervention
Category A	Person 1	Y_1	$Y_1(t)$
	Person 2	Y_2	$Y_2(t)$
	Person 3	Y_3	$Y_3(t)$
Category B	Person 4	Y_4	$Y_4(t)$
	Person 5	Y_5	$Y_5(t)$
	Person 6	Y_6	$Y_6(t)$
		Descriptive Disparity	**Gap-Closing Estimand**

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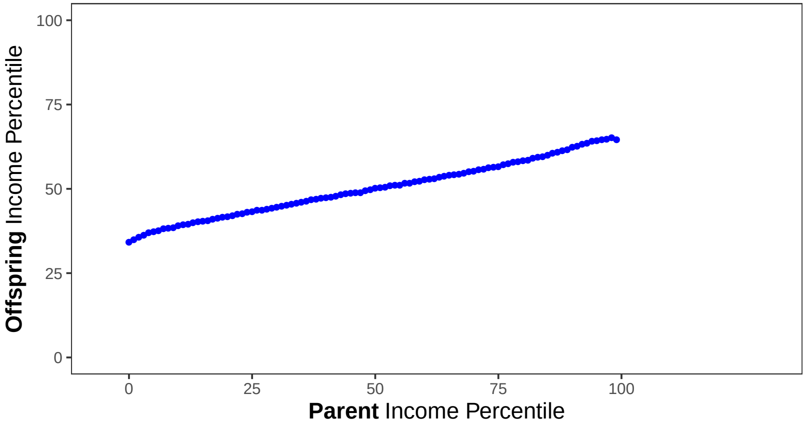
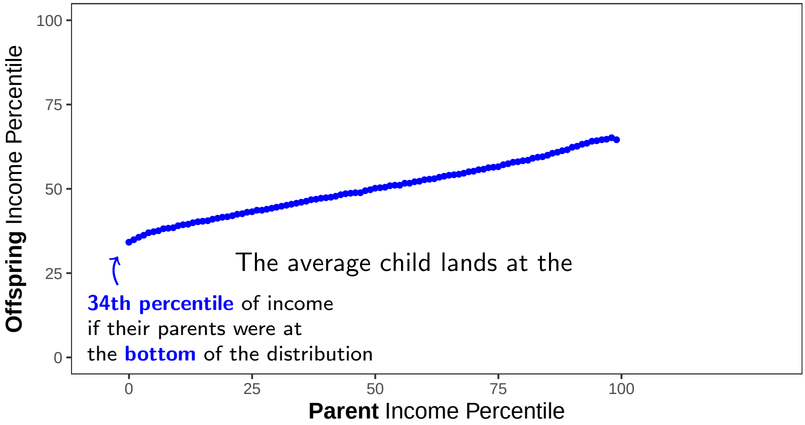
Jackson & Vanderweele 2018



Chetty et al. 2017



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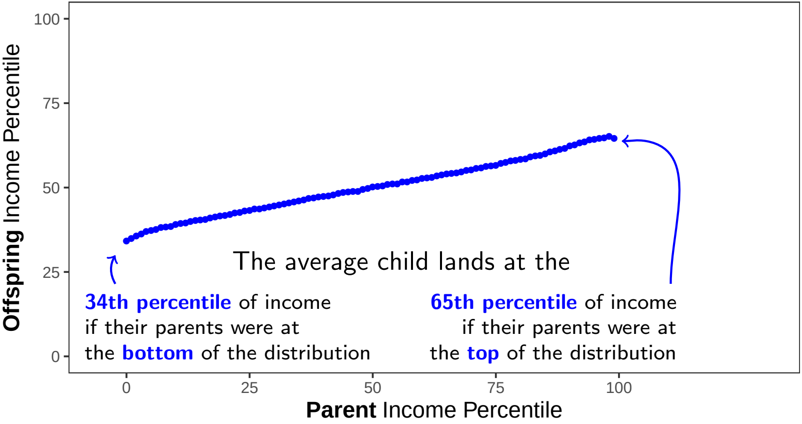

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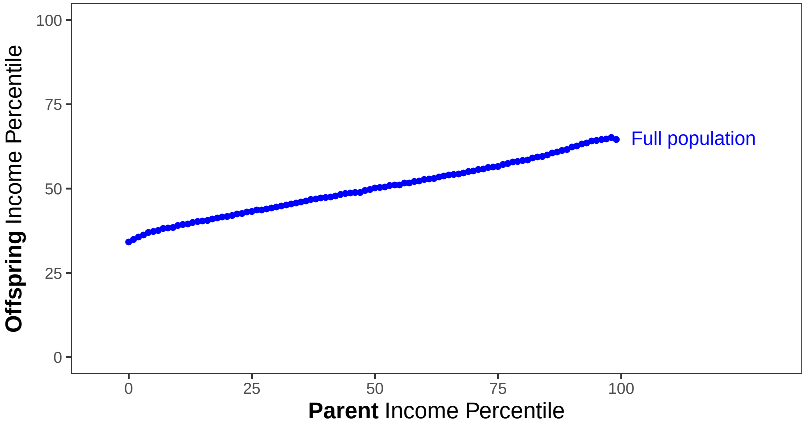

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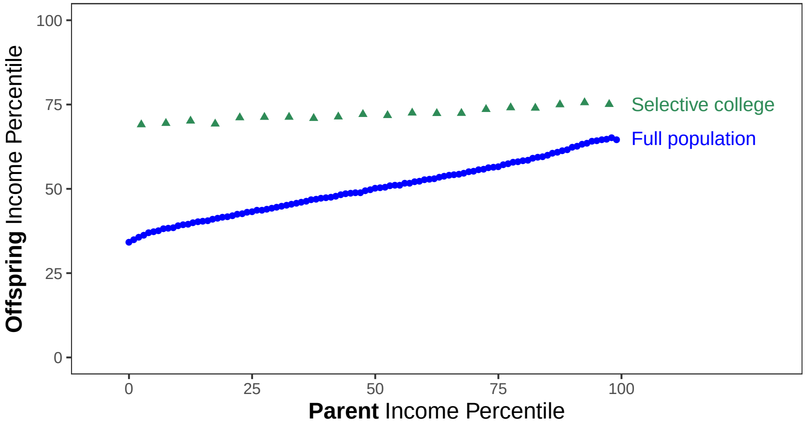

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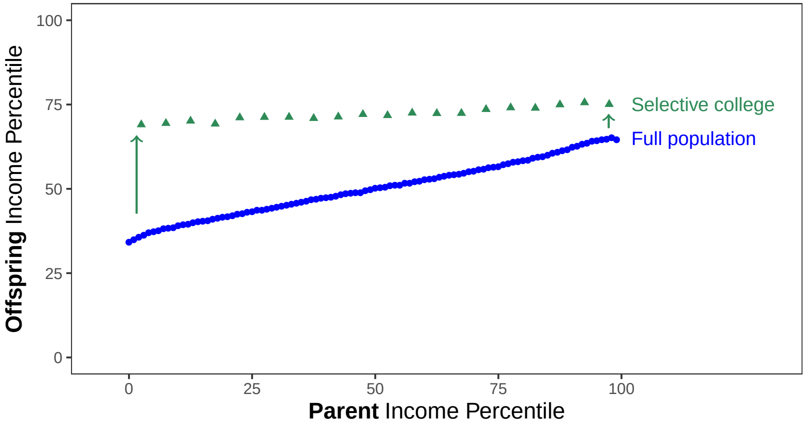

Chetty et al. 2017

Define the research goal by a **target trial** (Hernán & Robins 2016)

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

Define the research goal by a **target trial** (Hernán & Robins 2016)

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Goal: Result of this procedure

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

Difficulty: Causal inference

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Difficulty: Causal inference
Equilibrium dynamics

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Goal: Result of this procedure

Difficulty: Causal inference

Equilibrium dynamics

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Policy-relevant?

$\downarrow$

Local intervention

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

Difficulty: Causal inference

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Goal: Result of this procedure

Difficulty: Causal inference
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Prediction in Social Science

A Tool to Study Inequality in Populations

Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description — useful
3) Prediction for causal claims — opportunities abound

→ — Define the intervention
— Causal assumptions
— Estimation
— Empirical examples

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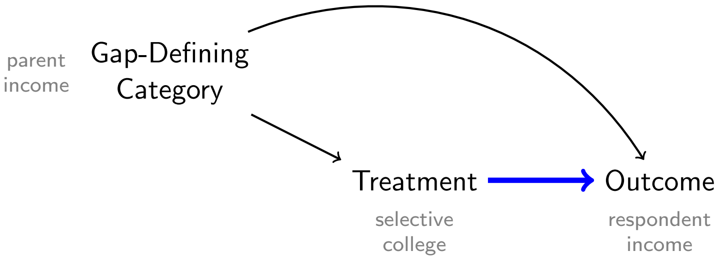
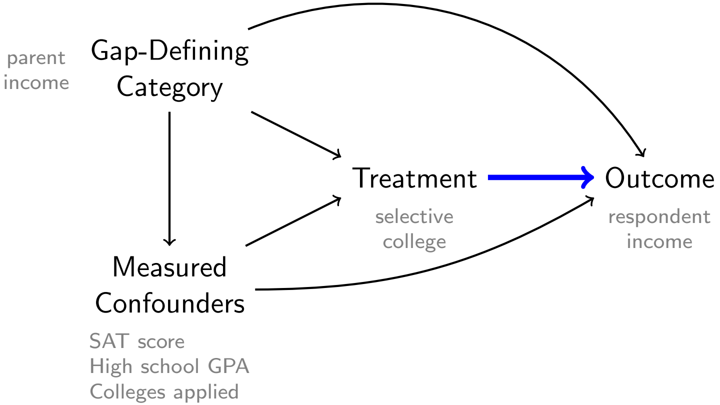
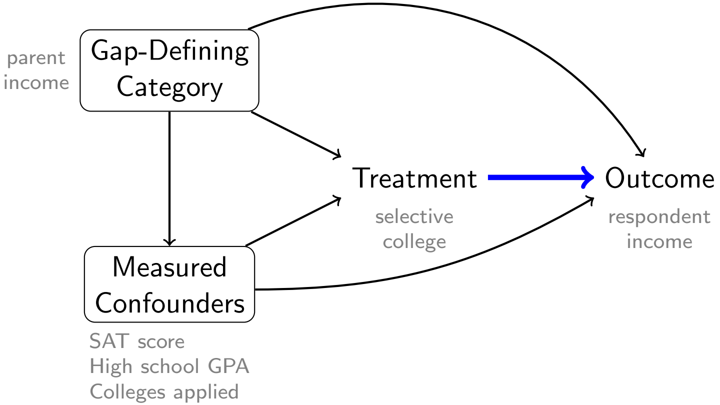

parent
income
Gap-Defining
Category
Treatment
Outcome
selective
college
respondent
income

Pearl 2009


parent
income
Gap-Defining
Category
Treatment
selective
college
Outcome
respondent
income
Measured
Confounders
SAT score
High school GPA
Colleges applied

Pearl 2009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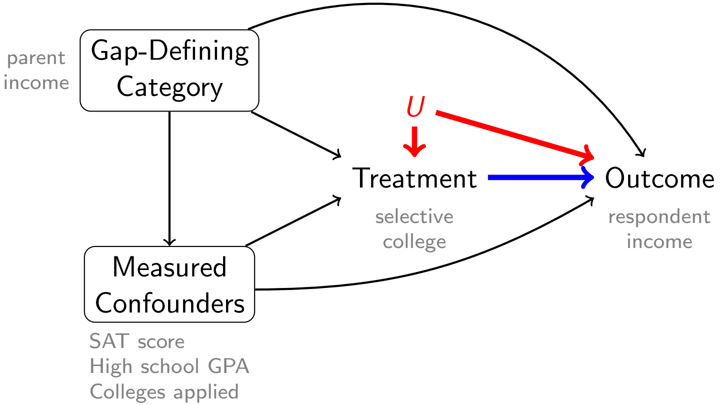
Pearl 2009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income
Gap-Defining
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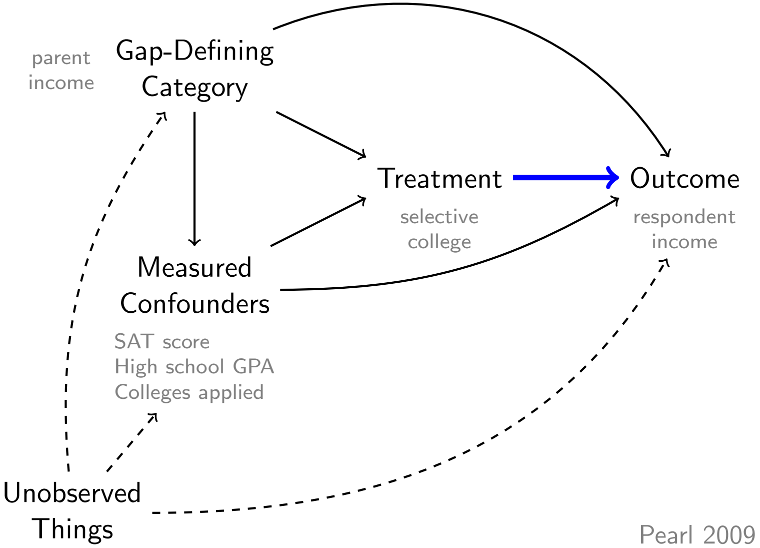

parent income
Gap-Defining Category
Treatment
selective college
Outcome
respondent income
Measured Confounders
SAT score
High school GPA
Colleges applied
Unobserved Things
Pearl 2009

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   - → — Estimation
   - — Empirical examples

		Prediction under treatment
People in category 1	Person 1	$\hat{Y}_1(1)$
	Person 2	$\hat{Y}_2(1)$
	Person 3	$\hat{Y}_3(1)$
People in category 2	Person 4	$\hat{Y}_4(1)$
	Person 5	$\hat{Y}_5(1)$
	Person 6	$\hat{Y}_6(1)$

		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	$\hat{Y}_6(1)$	?

		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	$\hat{Y}_6(1)$	?	?

		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	$\hat{Y}_6(1)$	?	?	

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	$\hat{Y}_1(1)$	?	?	
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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	$\hat{Y}_6(1)$	?	?	

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

New Estimate: (Original Estimate) − (Estimated Bias)

Doubly Robust Estimation

		Prediction under treatment	Outcome under treatment	Error	Weight on error
People in category 1	Person 1	$\hat{Y}_1(1)$	?	?	
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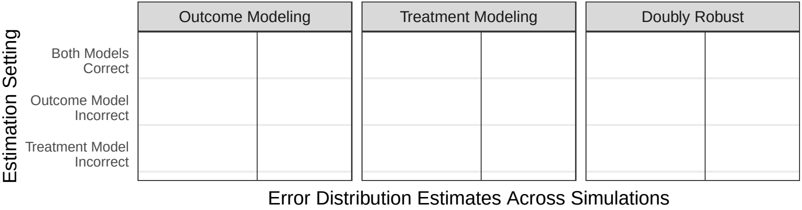

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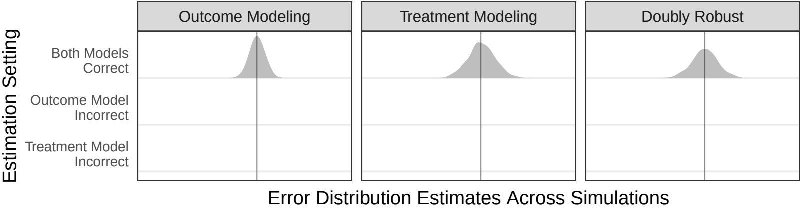

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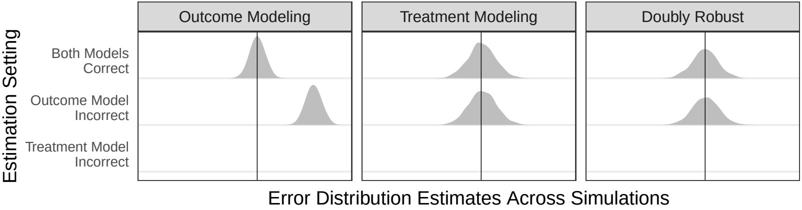

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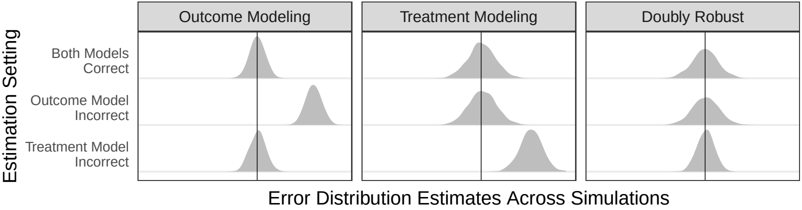

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Even better:

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Even better: — Learn $\hat{Y}_i$ in sample A

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Bickel 1982

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Even better:

— Learn $\hat{Y}_i$ in sample A

— Estimate bias in sample B

— Cross fit: Swap roles and average

Double Machine Learning

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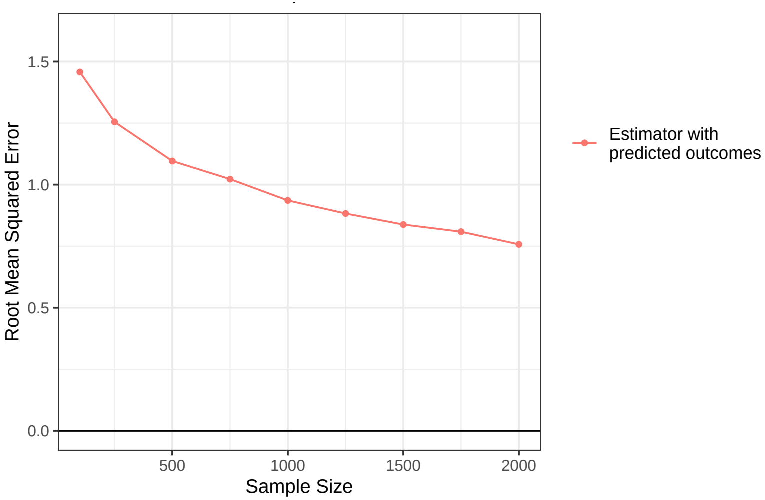
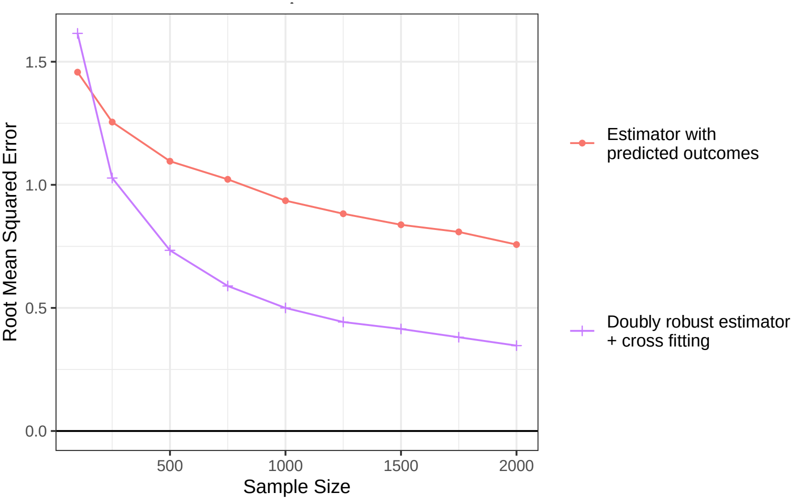

Root Mean Squared Error
1.5
1.0
0.5
0.0
500
1000
1500
2000
Sample Size
Estimator with predicted outcomes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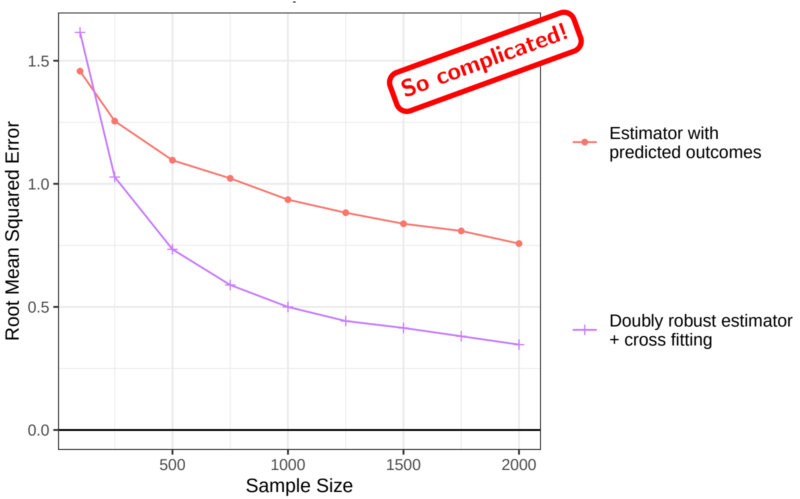
Doubly robust estimator + cross fitting



So complicated!
Root Mean Squared Error
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0.5
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gapclosing

R package for gap closing estimands

gapclosing

CRAN 1.0.1 downloads 314/month

Available from CRAN: `install.packages("gapclosing")`

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Available from CRAN: `install.packages("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
)
```

gapclosing

R package for gap closing estimands

gapclosing

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  sample_split = "cross_fit",
  se = T
)

Counterfactual mean outcomes (post-intervention means):
   category estimate     se ci.min ci.max
   <chr>       <dbl>  <dbl>  <dbl>  <dbl>
 1 A         -0.102  0.154  -0.404  0.200
 2 B          0.0409 0.0978 -0.151  0.233
```

Prediction in Social Science

A Tool to Study Inequality in Populations

Three possible uses:

1) Prediction for individuals — very hard
2) Prediction for description — useful
3) Prediction for causal claims — opportunities abound
   - — Define the intervention
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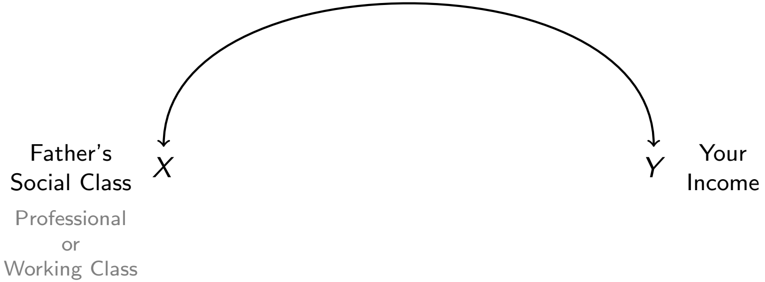

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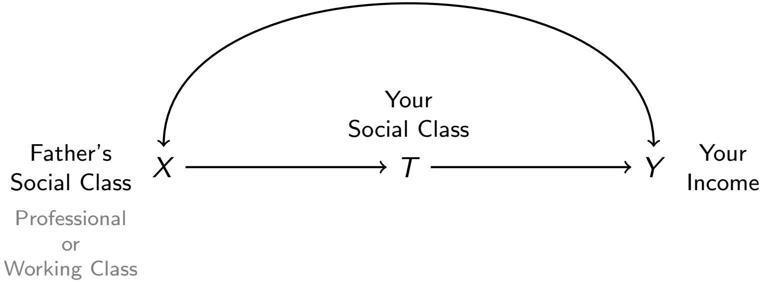

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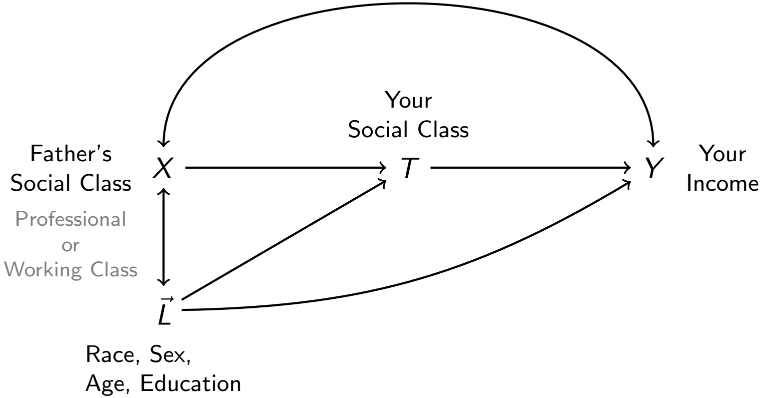

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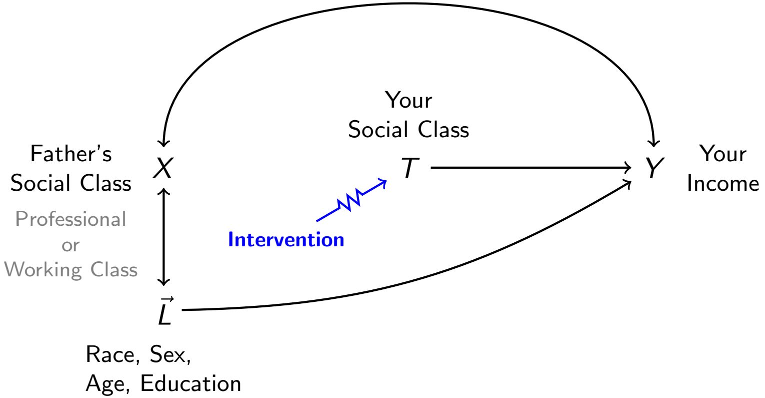

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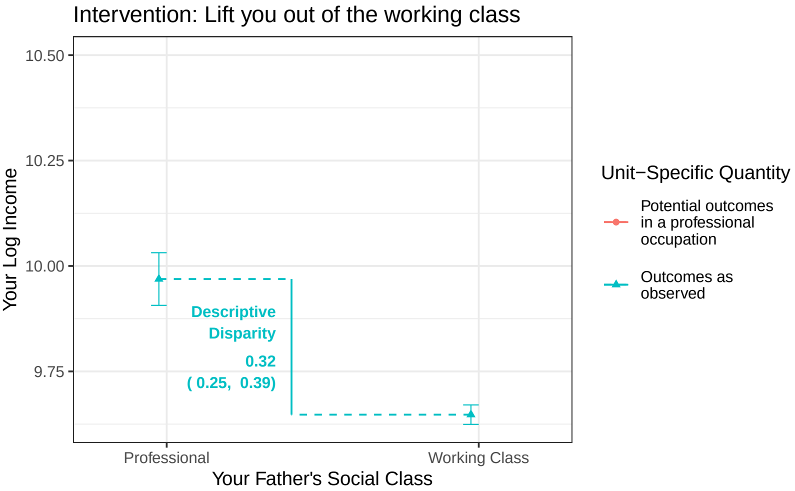

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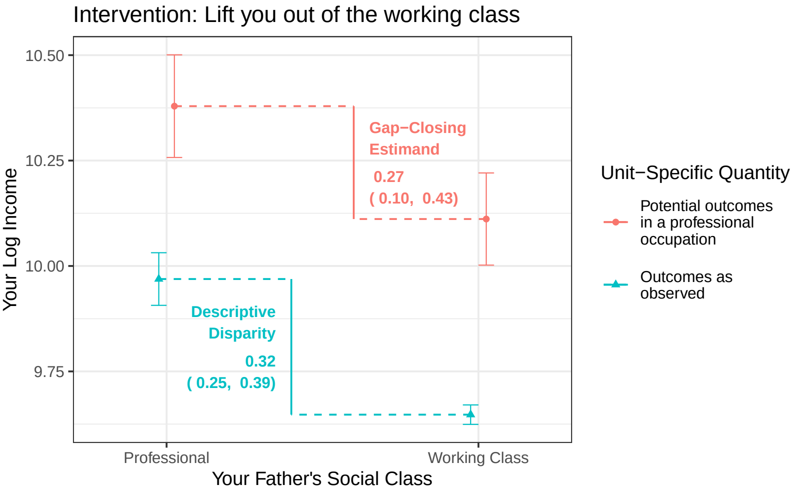

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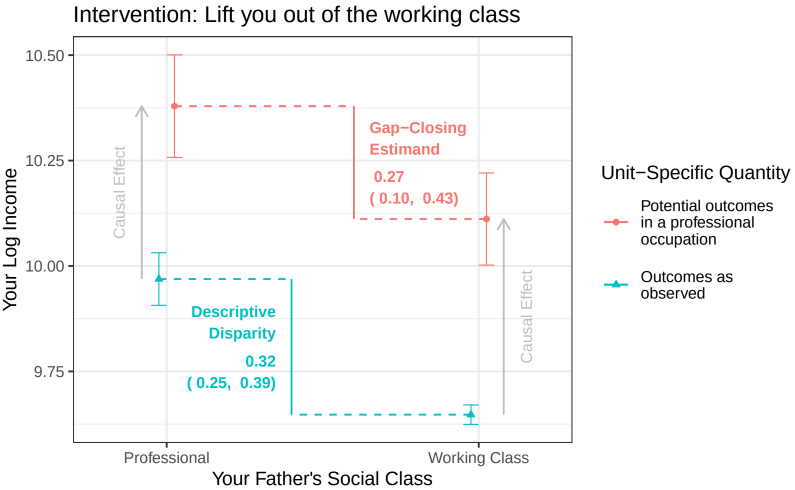
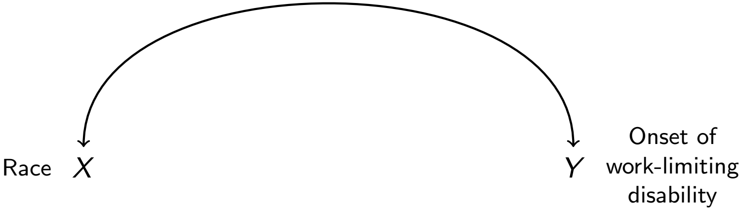


Empirical Example 2: Racial Disparities in Health



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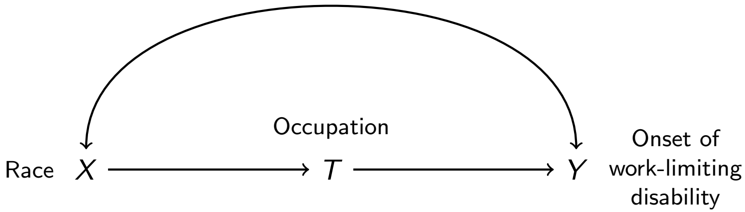

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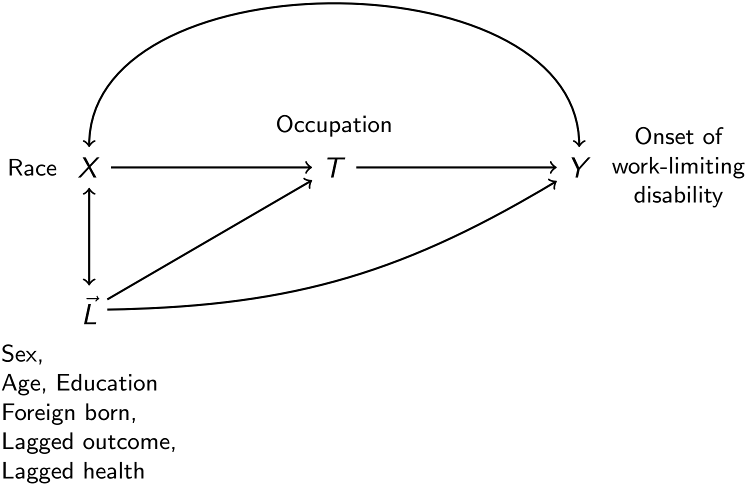

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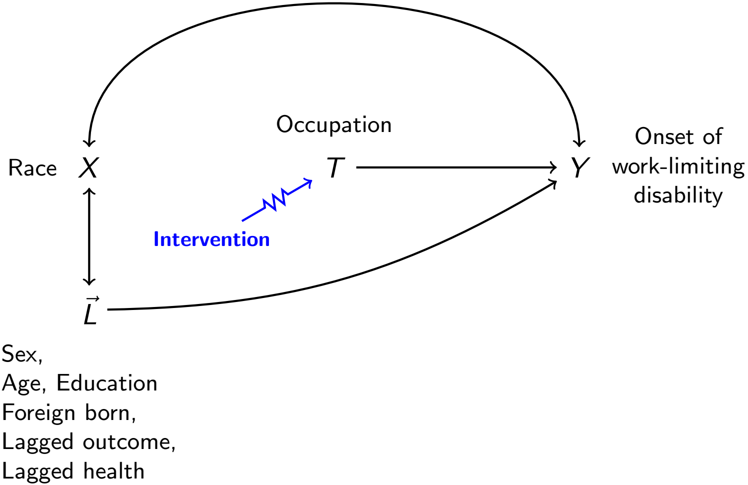

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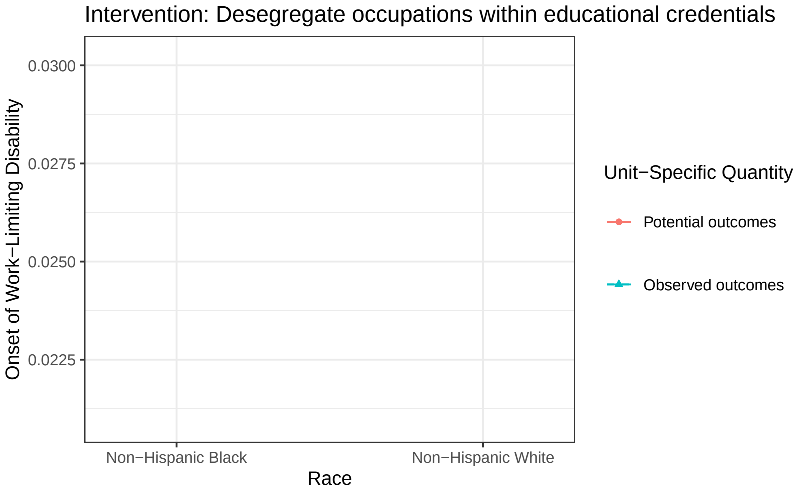

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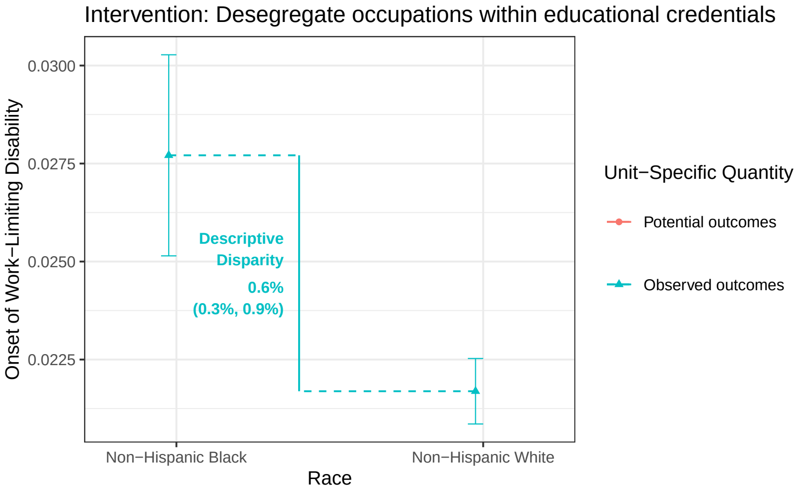

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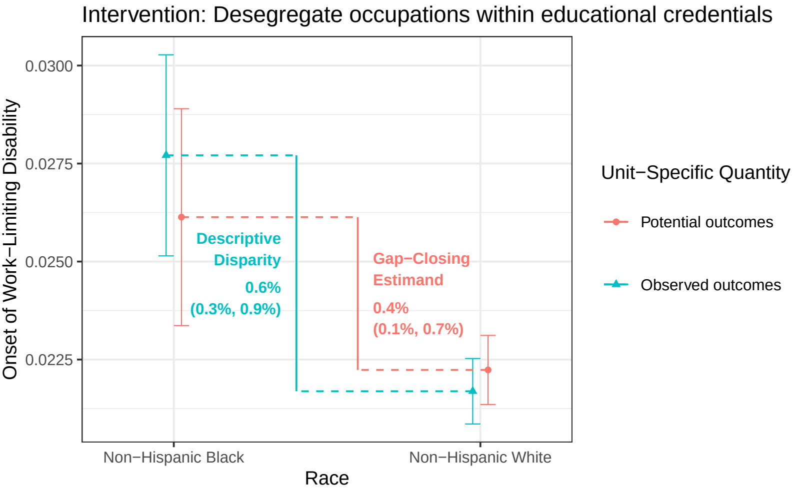

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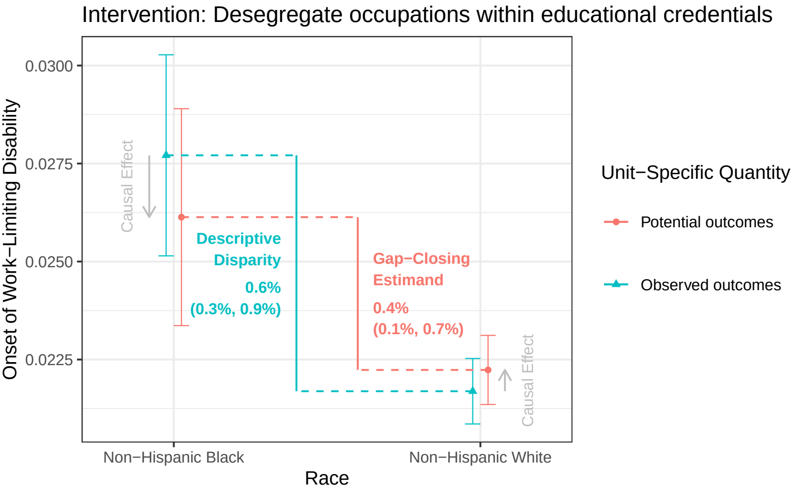

Future applications

The gap-closing estimand can help us understand disparities by

- Race
- Class
- Gender

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and develop interventions to **close those gaps**.

Contribution to methodology: Bringing perspectives together

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Interventions to Close Disparities
Biostatistics: Jackson & Vanderweele 2018

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Gap-Closing Estimand

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 $\longrightarrow$ Apple

 $\xrightarrow{\text{very difficult}}$ Evicted

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$\downarrow$

I take [data source]

I estimate β_1

$$Y = \beta_0 + X_1\beta_1 + X_2\beta_2 + \epsilon$$

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Epistemological crisis

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via **prediction**

Lundberg, Johnson, Stewart
What is Your Estimand?
Forthcoming, *American Sociological Review*

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$Y_i(t)$

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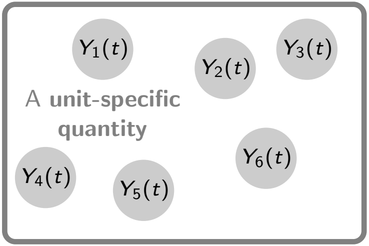

Aggregated over a **target population**

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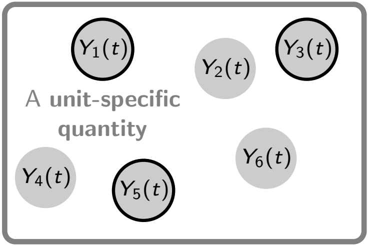

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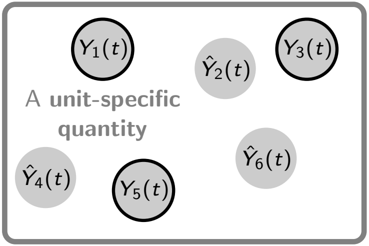

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Ian Lundberg
UCLA
ianlundberg.org

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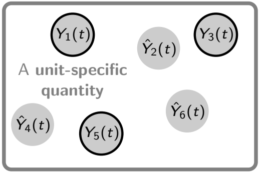


Aggregated over a **target population**

For replication code,
visit ianlundberg.org/cv.

APPENDIX

MSE proof

$$\text{MSE}\left(Y, \hat{Y}\right) = \text{E}\left(\left(Y - \hat{Y}\right)^2\right) \tag{1}$$

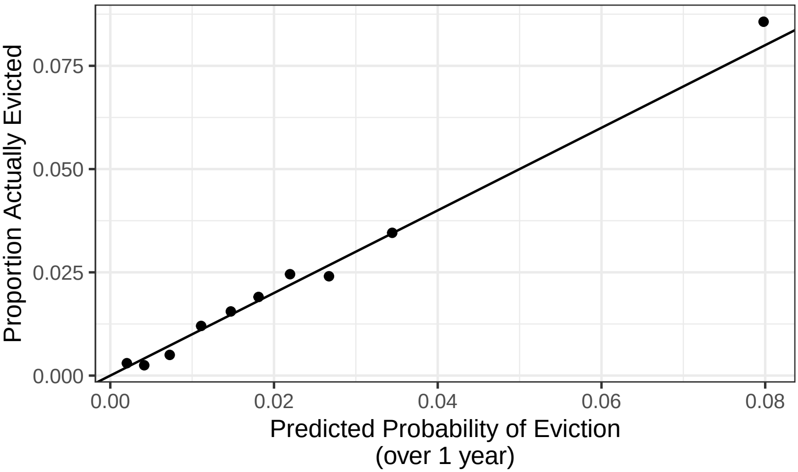
Add 0

$$= \text{E}\left(\left(Y - \text{E}(Y \mid \vec{X}) + \text{E}(Y \mid \vec{X}) - \hat{Y}\right)^2\right) \tag{2}$$

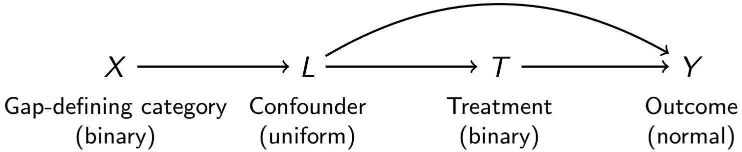
$$= \overbrace{\text{E}\left(\left(Y - \text{E}(Y \mid \vec{X})\right)^2\right)}^{=\text{E}\left(\text{V}(Y|\vec{X})\right)} + \overbrace{\text{E}\left(\left(\text{E}(Y \mid \vec{X}) - \hat{Y}\right)^2\right)}^{=\text{MSE}\left(\hat{Y},\text{E}(Y|\vec{X})\right)}$$
$$+ \underbrace{\text{E}\left(\left(Y - \text{E}(Y \mid \vec{X})\right)\left(\hat{Y} - \text{E}(Y \mid \vec{X})\right)\right)}_{=0 \text{ with sample splitting}} \tag{3}$$

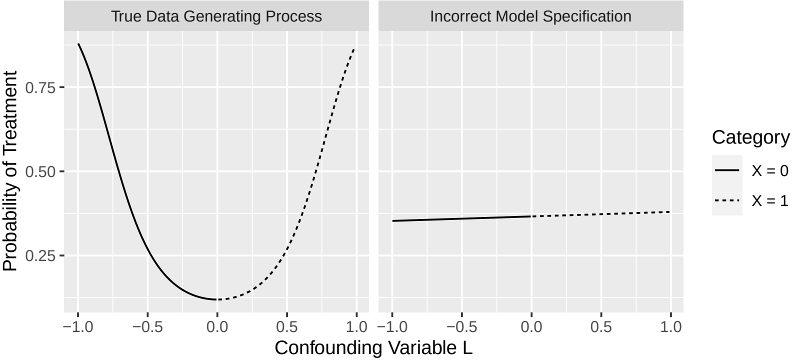
$$= \text{E}\left(\text{V}(Y \mid \vec{X})\right) + \text{MSE}\left(\hat{Y}, \text{E}(Y \mid \vec{X})\right) \tag{4}$$

Calibration of eviction probabilites



Simulated details for doubly robust GLMs



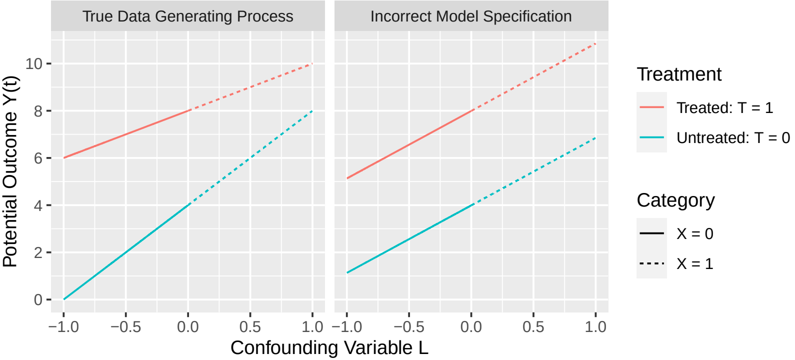


Simulated details for doubly robust GLMs

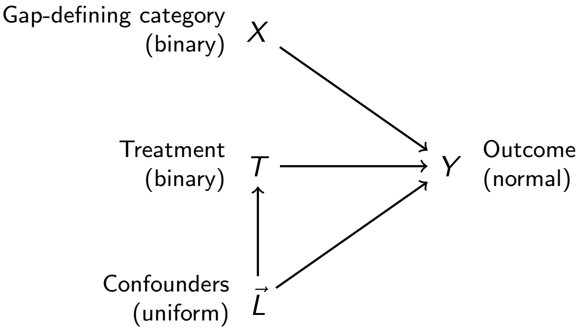
$$X \longrightarrow L \longrightarrow T \longrightarrow Y$$

with an additional arrow $L \to Y$.

Gap-defining category (binary)	Confounder (uniform)	Treatment (binary)	Outcome (normal)



Simulated details for cross-fitting



- True outcome model is linear and additive
- True treatment model is additive logistic regression

Simulation details for cross-fitting

$$X \sim \text{Bernoulli}(.5) \tag{5}$$

$$L_1, \dots, L_{10} \sim \text{Uniform}(-1, 1) \tag{6}$$

$$m(1, X, \vec{L}) = \begin{cases} \text{logit}^{-1}\left(.1L_1 + \dots + .1L_{10}\right) & \text{if } X = 1 \\ \text{logit}^{-1}\left(.3L_1 + \dots + .3L_{10}\right) & \text{if } X = 0 \end{cases} \tag{7}$$

$$T \sim \text{Bernoulli}\left(m(1, X, \vec{L})\right) \tag{8}$$

$$g(T, X, \vec{L}) = \begin{cases} L_1 + \dots + L_{10} + T & \text{if } X = 1 \\ L_1 + \dots + L_{10} - T & \text{if } X = 0 \end{cases} \tag{9}$$

$$Y \sim \text{Normal}\left(\text{Mean} = g(T, X, \vec{L}), \text{SD} = 10\right) \tag{10}$$

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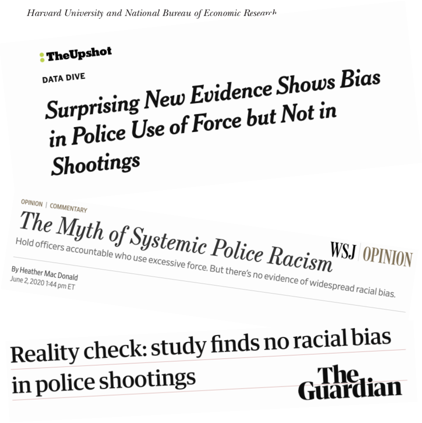
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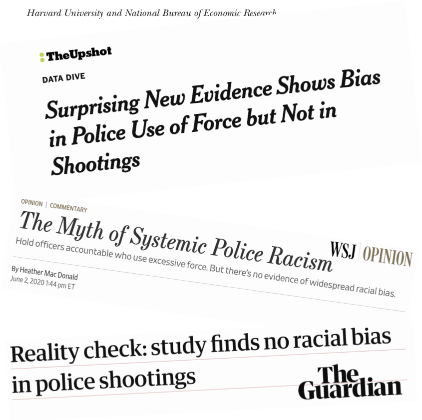

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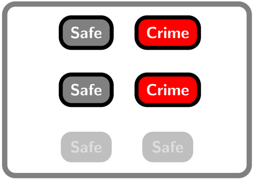
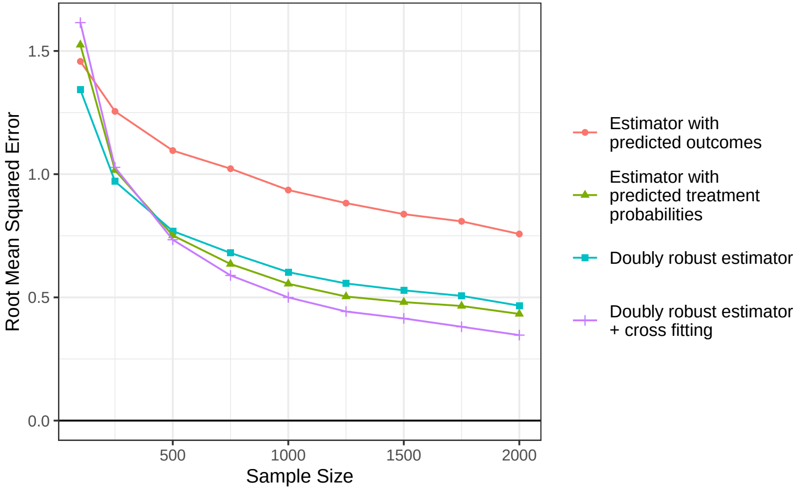
Perceived as **black**



Perceived as **white**

Equal use of force among those stopped is actually **consistent** with bias

See Knox et al. 2020 for a fuller critique


Root Mean Squared Error
1.5
1.0
0.5
0.0
500
1000
1500
2000
Sample Size
Estimator with predicted outcomes
Estimator with predicted treatment probabilities
Doubly robust estimator
Doubly robust estimator + cross fitting