19. Bringing Ideas Together: What is Your Estimand?

Ian Lundberg
Cornell Info 6751: Causal Inference in Observational Settings
Fall 2022

27 Oct 2022

Learning goals for today

At the end of class, you will be able to:

1. Connect key concepts from this class to issues in social science today
2. Be ready to apply those concepts in your research proposal

Where we are in the course

Core Ideas (Cumulative)

Select Topics (Not Cumulative)

Schedule of Topics

Part 1. Inference without models.		
Aug 23.	Causal questions: Observing and intervening	Hernán and Robins (2020) Ch 1 [pdf]
Aug 25.	The target trial	Hernán (2016) [pdf]
Aug 30.	Consistency: Defining potential outcomes	Hernán and Robins (2020) 3.4–3.5 [pdf]
Sep 1.	Sharp bounds and the limits of assumption-free inference	Mullahy et al. (2021) [pdf]
Sep 6.	Exchangeability: Assumptions to block backdoor paths	Greenland et al. (1999) [pdf]
Sep 8.	Population-average causal effects from samples	Westreich et al. (2019) [pdf]
Sep 13.	Positivity: Recognizing the problem of empty cells	Hernán and Robins (2020) 3.3 [pdf]
Part 2. Inference with models.		
Sep 15.	The parametric g-formula: Categorical treatments	Hernán and Robins (2020) Ch 13 [pdf]
Sep 20.	The parametric g-formula: Continuous treatments	Rothenhäusler and Yu (2019) [pdf]
Sep 22.	The generality of the g-formula: Using any estimator	Dorie et al. (2019), [pdf]
Sep 27.	The g-formula by matching	Stuart (2010) [pdf]
Sep 29.	The g-formula with propensity scores	Brand and Xie (2010) [pdf]
Oct 4.	Inverse probability weighting	Hernán and Robins (2020) 12.1-12.3 [pdf]
Oct 6.	Marginal structural models	Hernán and Robins (2020) 12.4-12.6 [pdf]
Part 3. Dynamic causal inference.		
Oct 13.	Treatments in many time periods	Hernán and Robins (2020) Ch 19.(1,2,3), 20 [pdf]
Oct 18.	Estimation for treatments in many periods	Hernán and Robins (2020) Ch 19.4, 21.(1,2,4) [pdf]
Oct 20.	Mediation: Controlled direct effects	Acharya et al. (2016) [pdf]
Oct 25.	Mediation: Natural direct and indirect effects	Imai et al. (2011) [pdf]
Part 4. Complexities that arise in real settings.		
Oct 27.	Defining the estimand is hard	Lundberg et al. (2021) [pdf]
—Deadline. Ideas for the research proposal due Oct 31—		
Nov 1.	Principal stratification: Addressing undefined outcomes	Page et al. (2015) [pdf]
Nov 3.	Principal stratification: Bias in policing	Knox et al. (2020) [pdf]
Nov 8.	Unknown functional forms: Two chances	Glynn and Quinn (2010) [pdf]
Nov 10.	Measurement error: The problem	Hernán and Cole (2009) [pdf]
Nov 15.	Measurement error: Using proxies	Elwert and Pfeffer (2022) [pdf]
Nov 17.	Class guest: Felix Elwert. Discuss “The Future Strikes Back.”	
—Deadline. Final research proposal due Nov 21—		
Nov 22.	Beyond backdoor adjustment: Regression discontinuity	De la Cuesta and Imai (2016) [pdf]
Nov 24.	[No class. Thanksgiving.]	
Nov 29.	Beyond backdoor adjustment: Instrumental variables	Hernán and Robins (2020) Ch 16 [pdf]
Dec 1.	Course recap: Causal inference in observational settings	
—Deadline. Feedback to two peers due Dec 5—		

Where we are in the course

Core Ideas (Cumulative)

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What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

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Rebecca Johnson
Georgetown
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Princeton
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brandonstewart.org

27 September 2022. Cornell Info 6751.
Paper in *American Sociological Review* [link]. Open access on SocArxiv. Replication code on Dataverse. 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.

There is a question every quantitative study must answer:

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A common answer:

— We took [data source]

— We estimated β_1

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

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A **unit-specific quantity**

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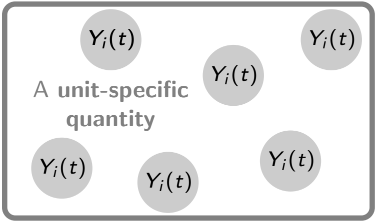

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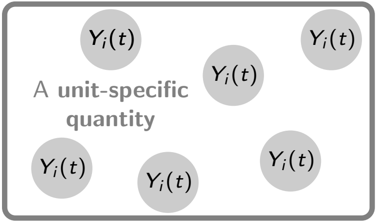

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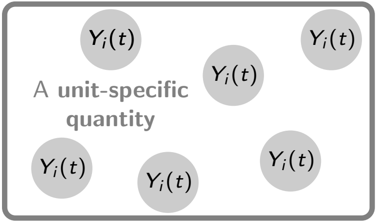

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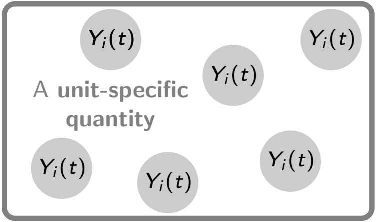

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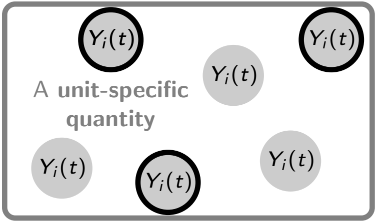

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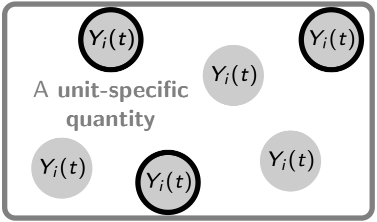

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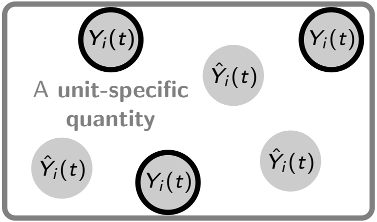

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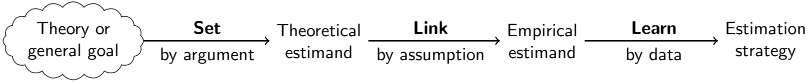


What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

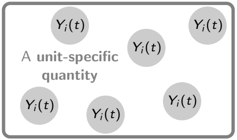
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



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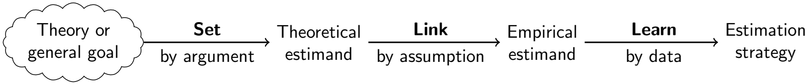

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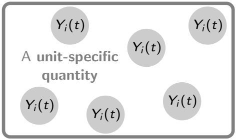

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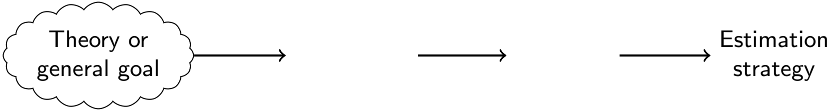
Research framework: Estimands connect theory to evidence



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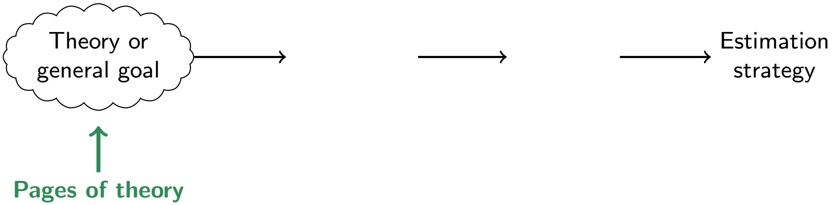

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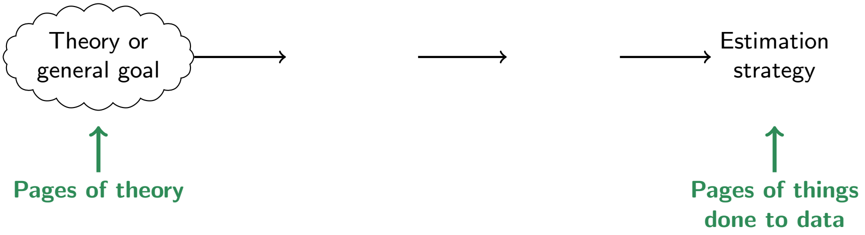

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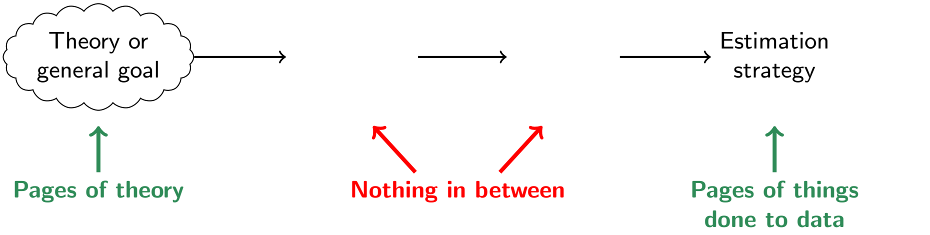

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Theory or general goal $\longrightarrow$ Theoretical estimand $\longrightarrow$ Empirical estimand $\longrightarrow$ Estimation strategy

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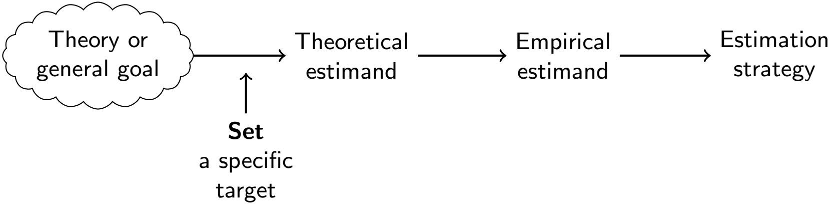

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Set a specific target

Definition

A **unit-specific quantity** aggregated over a **target population**

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Set a specific target

Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$\frac{1}{\substack{\text{Size of U.S.}\\ \text{adult population}}} \sum_{\substack{i \text{ in U.S.}\\ \text{adult population}}} \left(\text{Employed}_i\right)$

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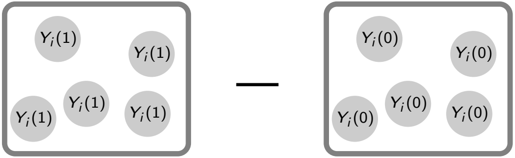

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Link to observable data

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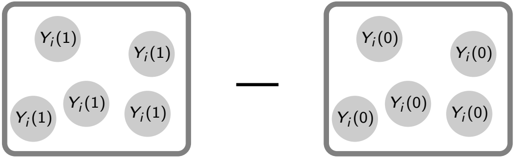
A quantity involving **observable data**	

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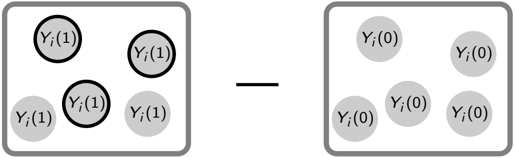
A quantity involving **observable data**	

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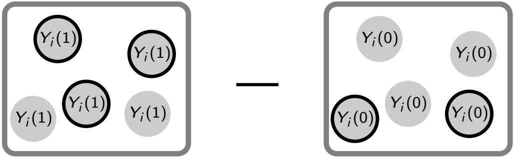
A quantity involving **observable data**	

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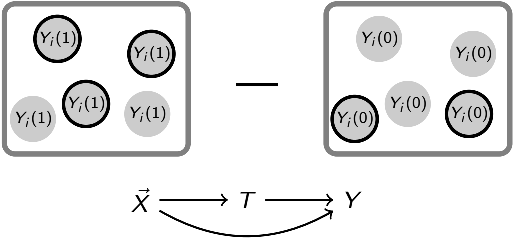

Pearl 2009, Imbens and Rubin 2015,
Morgan and Winship 2015, Elwert and Winship 2014

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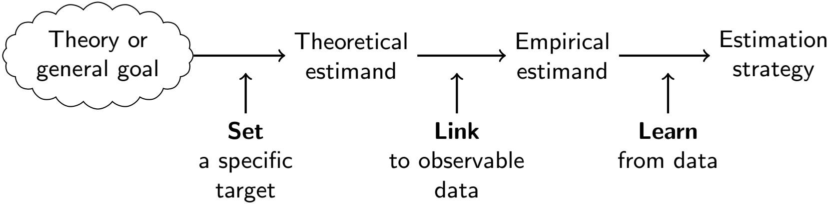

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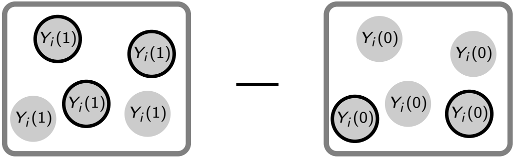
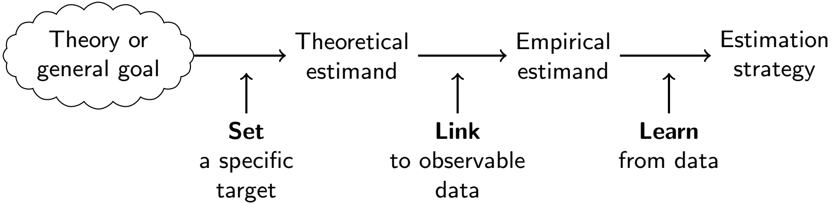
An algorithm applied to data	

Lundberg, Johnson, and Stewart. What is Your Estimand?

Research framework: Estimands connect theory to evidence



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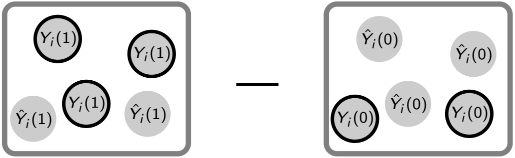
An algorithm applied to data	

Young 2009, Watts 2014, Berk et al. 2019, Molina and Garip 2019

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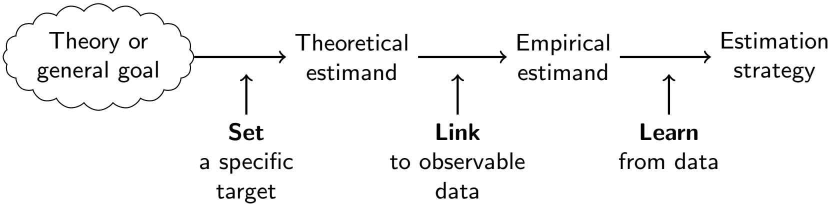

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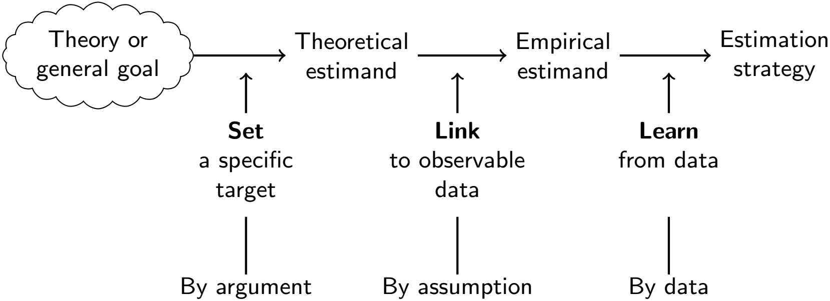

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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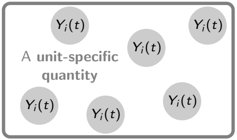
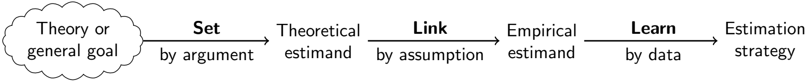
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



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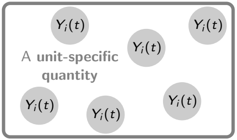

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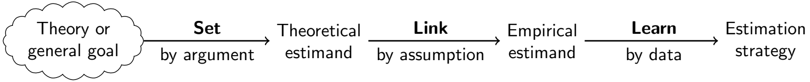

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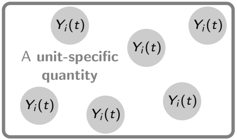

Averaged over a **target population**

Pager (2003) explores

"the ways in which
the effects of race and
criminal record interact to
produce new forms
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Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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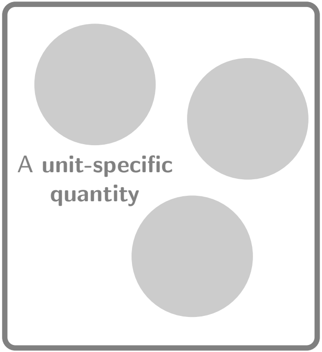

Averaged over a
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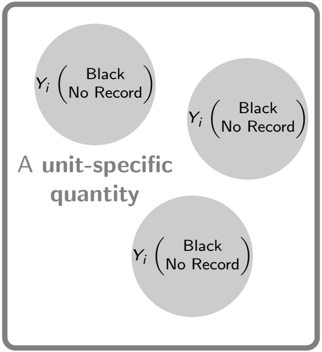

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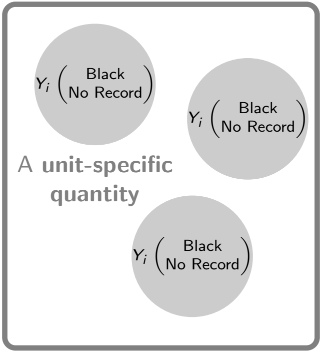
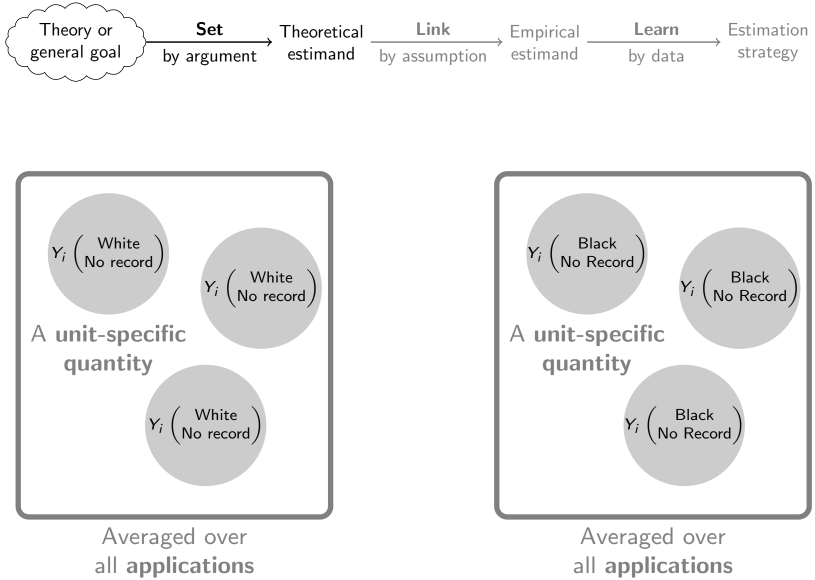


Averaged over all **applications**

Key insight:
Each unit *i* is an application, not a person.

Greiner & Rubin 2011, Sen & Wasow 2016, Kohler-Hausmann 2018


Theory or general goal
Set
by argument
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Link
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Learn
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Estimation strategy
$Y_i\begin{pmatrix}\text{White}\\\text{No record}\end{pmatrix}$
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$Y_i\begin{pmatrix}\text{White}\\\text{No record}\end{pmatrix}$
A **unit-specific quantity**
Averaged over all **applications**
$Y_i\begin{pmatrix}\text{Black}\\\text{No Record}\end{pmatrix}$
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A **unit-specific quantity**
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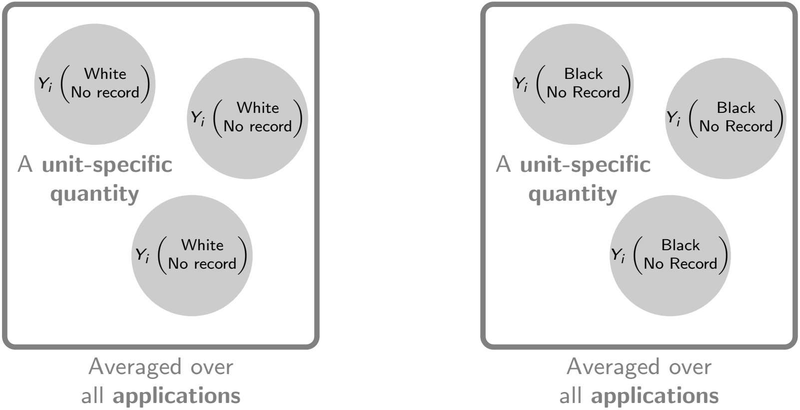
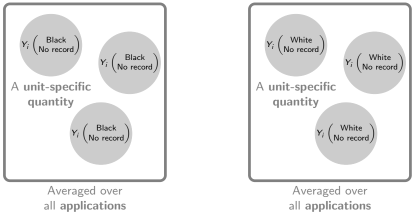
Discrimination: One population of applications

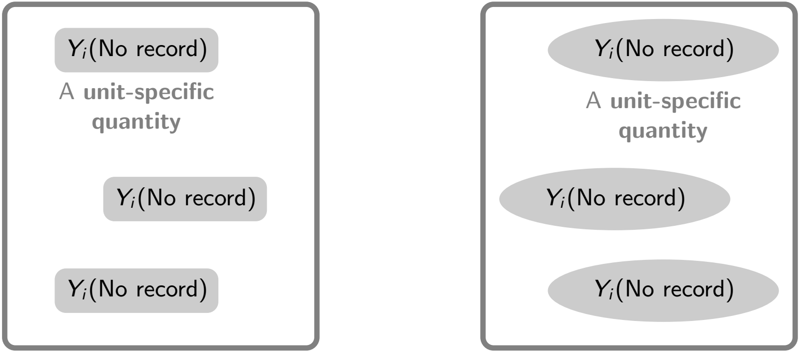


Estimand 1: Racial **discrimination**



Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

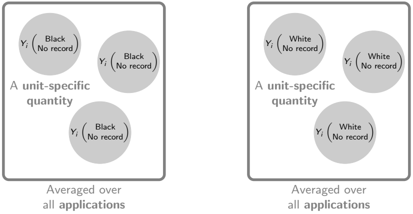
Estimand 2: Racial **disparity** if we eliminated criminal records



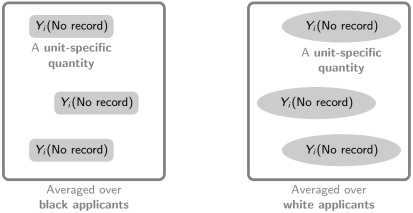
Averaged over **black applicants**

Averaged over **white applicants**

Estimand 1: Racial **discrimination**



Estimand 2: Racial **disparity** if we eliminated criminal records



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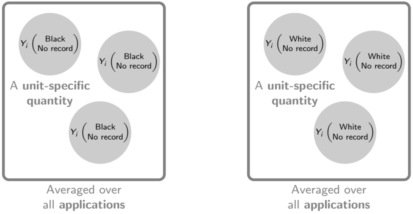
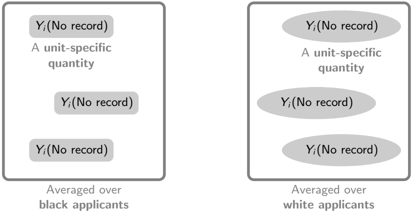


Two treatment conditions

One population

Estimand 2: Racial **disparity** if we eliminated criminal records



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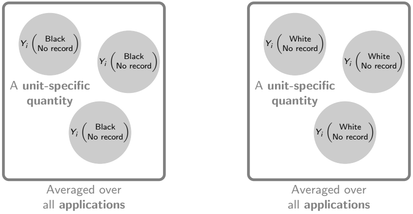

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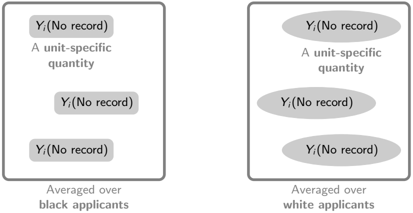

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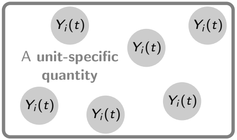

Averaged over a **target population**

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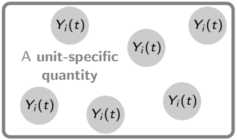

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Angrist and Evans 1998

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Effect of motherhood
on employment

Angrist and Evans 1998

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Effect of motherhood
on employment

First two births
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Effect of motherhood
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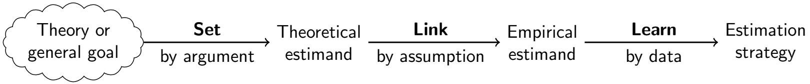
First two births are the same sex $\longrightarrow$ Third birth

Angrist and Evans 1998



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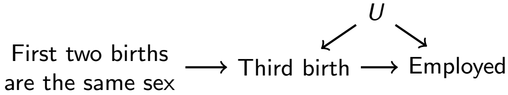

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Vague estimand

Effect of motherhood
on employment

$$
\begin{tikzcd}
 & & U \arrow[dl] \arrow[dr] & \\
\text{First two births are the same sex} \arrow[r] & \text{Third birth} \arrow[rr] & & \text{Employed}
\end{tikzcd}
$$

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Vague estimand

Effect of motherhood on employment

Precise estimand

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unit-specific quantity

Vague estimand

Effect of motherhood on employment

Precise estimand

Effect of having **3 vs. 2 children**

$$\begin{tikzcd} & & U \arrow[dl] \arrow[dr] & \\ \text{First two births are the same sex} \arrow[r] & \text{Third birth} \arrow[rr] & & \text{Employed} \end{tikzcd}$$

Angrist and Evans 1998

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Vague estimand

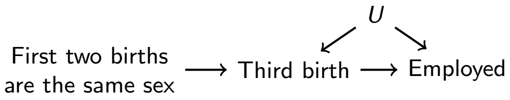
Effect of motherhood on employment

target population

Precise estimand

Effect of having 3 vs. 2 children

[among those with at least two children who would have a third birth if and only if the first two were of the same sex]



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Precise estimand

Effect of having 3 vs. 2 children

among those with at least two children who would have a third birth if and only if the first two were of the same sex

$\approx$ 4% of all mothers

Angrist and Evans 1998

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You have to argue either:

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2)

Angrist and Evans 1998

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You have to argue either:

1) That estimand matters for theory, or

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Angrist and Evans 1998

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Effect of having 3 vs. 2 children

among those with at least two children who would have a third birth if and only if the first two were of the same sex

$\approx$ 4% of all mothers

You have to argue either:

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2) It speaks to some broader estimand

Angrist and Evans 1998

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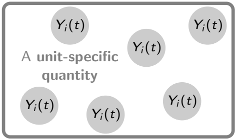

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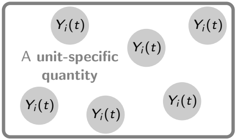

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Example: Age-standardized mortality

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1. Estimate mortality in the U.S. and Mexico at each age.

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Example: Age-standardized mortality

1. Estimate mortality in the U.S. and Mexico at each age.
2. Aggregate over the U.S. age distribution.

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Example: Age-standardized mortality

1. Estimate mortality in the U.S. and Mexico at each age.
2. Aggregate over the U.S. age distribution.
3. Report the disparity between the two countries.

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Descriptive Estimand

Causal Estimand

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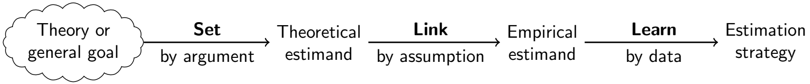
Age-specific mortality
is descriptive

Causal Estimand



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Aggregation is a simple summary

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Why not obesity,

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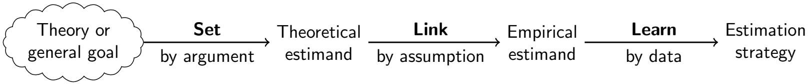
Identified ✓



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Meaningful ?

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2. Aggregate over the U.S. age distribution.
3. Report the disparity between the two countries.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

The "effect" of social context

Identified ✓

Meaningful ?

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A "counterfactual" population

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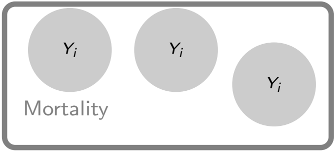

Averaged over the U.S. population

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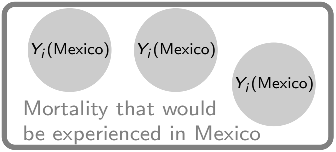

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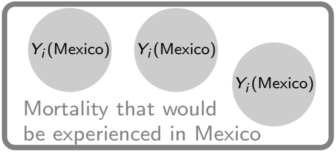

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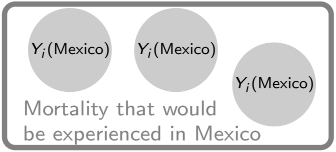

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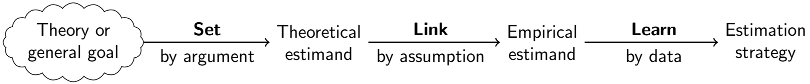

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This same issue applies to
all sociological studies
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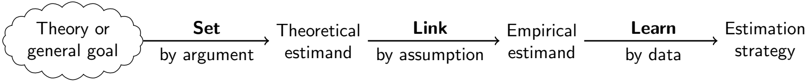

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
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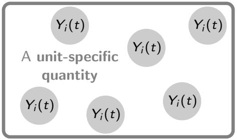
Document widespread vagueness in *ASR*

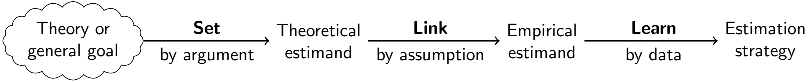
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



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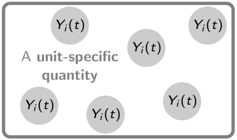

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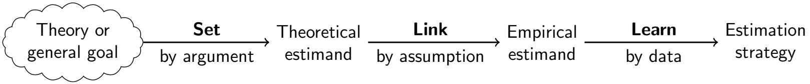

An Empirical Analysis of Racial Differences in Police Use of Force

Roland G. Fryer Jr.

Harvard University and National Bureau of Economic Research

This paper explores racial differences in police use of force. On non-lethal uses of force, blacks and Hispanics are more than 50 percent more likely to experience some form of force in interactions with police. Adding controls that account for important context and civilian behavior reduces, but cannot fully explain, these disparities. On the most extreme use of force—officer-involved shootings—we find no racial differences either in the raw data or when contextual factors are taken into account. We argue that the patterns in the data are consistent with a model in which police officers are utility maximizers, a fraction of whom have a preference for discrimination, who incur relatively high expected costs of officer-involved shootings.

> We can never be satisfied as long as the Negro is the victim of the unspeakable horrors of police brutality. (Martin Luther King Jr., August 28, 1963)

I. Introduction

From "Bloody Sunday" on the Edmund Pettus Bridge to the public beatings of Rodney King, Bryant Allen, and Freddie Helms, the relationship

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Electronically published April 22, 2019
[*Journal of Political Economy*, 2019, vol. 127, no. 3]
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TheUpshot

DATA DIVE

Surprising New Evidence Shows Bias in Police Use of Force but Not in Shootings

Lundberg, Johnson, and Stewart. What is Your Estimand?

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OPINION | COMMENTARY

The Myth of Systemic Police Racism

WSJ | OPINION

Hold officers accountable who use excessive force. But there's no evidence of widespread racial bias.

By Heather Mac Donald
June 2, 2020 1:44 pm ET

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Reality check: study finds no racial bias in police shootings

The Guardian

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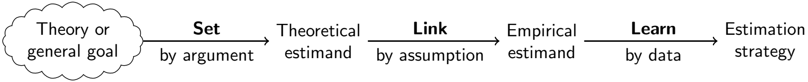
Evidence:

Claim:

Why wrong:

Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



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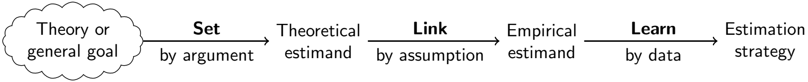

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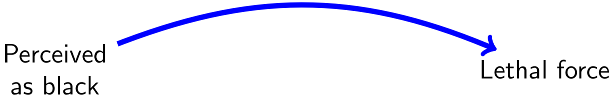

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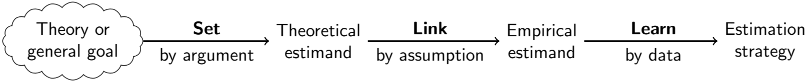

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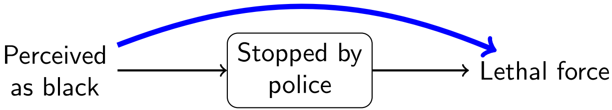

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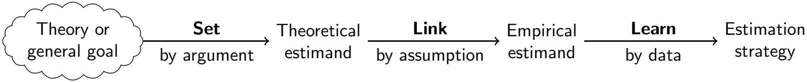

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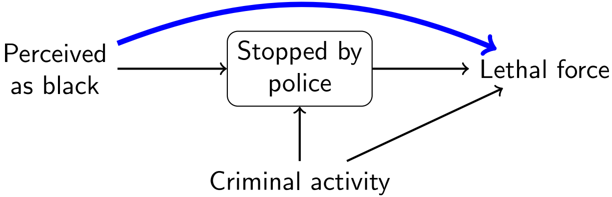

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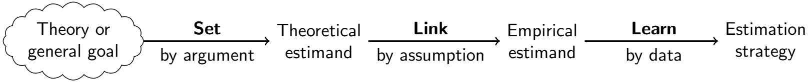

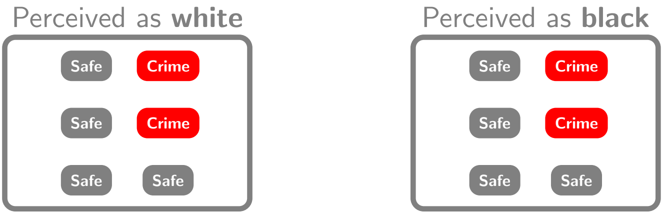

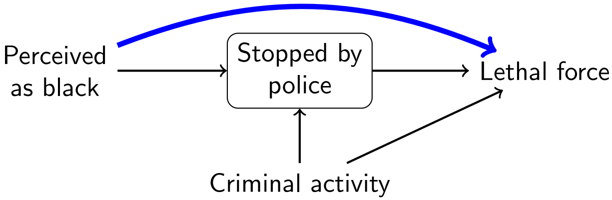

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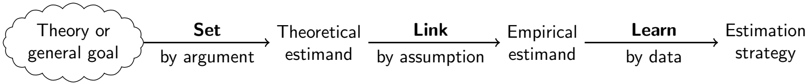

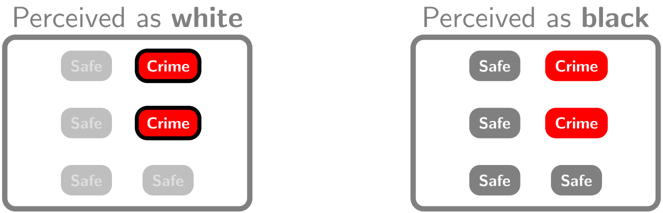

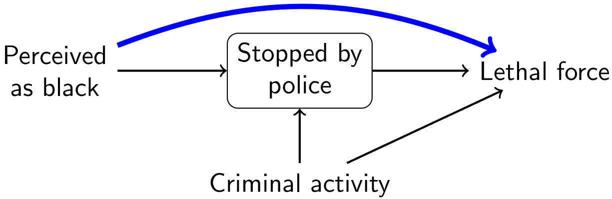

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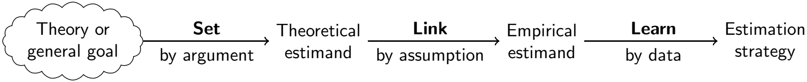

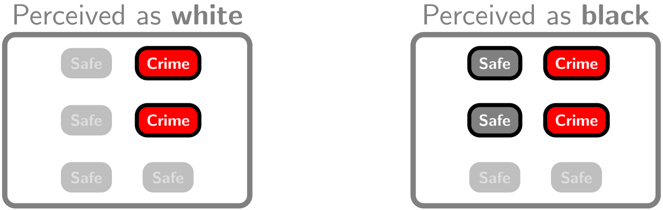

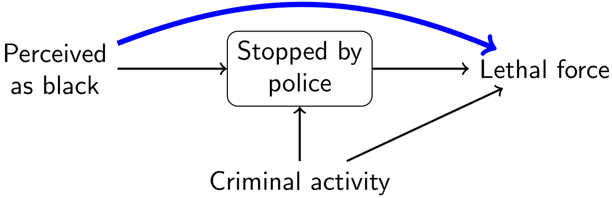

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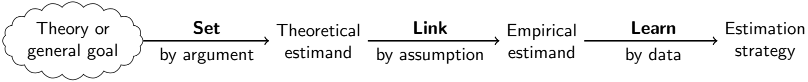

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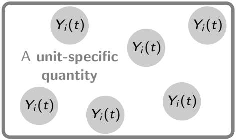

Averaged over a **target population**

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

→ **Document** widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

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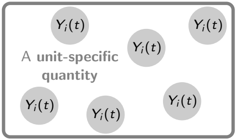

Averaged over a **target population**

$$\text{Theory or general goal} \xrightarrow[\text{by argument}]{\textbf{Set}} \text{Theoretical estimand} \xrightarrow[\text{by assumption}]{\textbf{Link}} \text{Empirical estimand} \xrightarrow[\text{by data}]{\textbf{Learn}} \text{Estimation strategy}$$

Review

All 32 articles in ASR 2018 using quantitative data

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Review

All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles / 56% of *ASR*	7 articles / 22% of *ASR*	7 articles / 22% of *ASR*
Causal target: Observational data	Causal target: Experiments	Descriptive target

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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0 out of 18 articles was clear	**4 out of 7** articles were clear	**1 out of 7** articles was clear

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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All 32 articles in ASR 2018 using quantitative data

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Clarity about the **target population**

3 types of articles with distinct issues

16 articles | 50% of *ASR*
6 articles | 19% of *ASR*
10 articles | 31% of *ASR*

Probability samples | Administrative records | Other samples

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

Review
All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles, 56% of *ASR*	7 articles, 22% of *ASR*	7 articles, 22% of *ASR*
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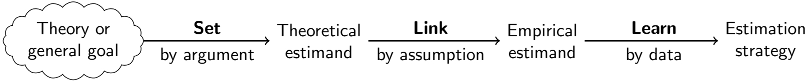
Clarity about the **target population**

3 types of articles with distinct issues

16 articles, 50% of *ASR*	6 articles, 19% of *ASR*	10 articles, 31% of *ASR*
Probability samples	Administrative records	Other samples
6 out of 16 articles were clear	**1 out of 6** articles was clear	**2 out of 10** articles were clear



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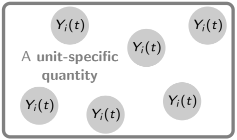
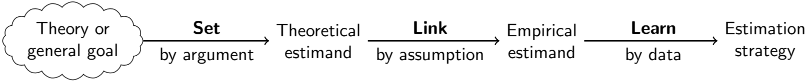


Averaged over a **target population**



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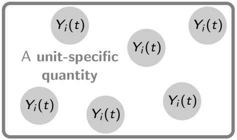

Averaged over a **target population**

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Replication 1

- Define a tricky theoretical estimand
- Reveal overlooked identification assumptions
- Show the mechanics of estimation by machine learning

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Pal and Waldfogel (2016) estimate the family gap in pay.

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Is the theoretical estimand descriptive?

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Is the theoretical estimand descriptive?

"the differential in hourly wages
between women with children
and women without children"

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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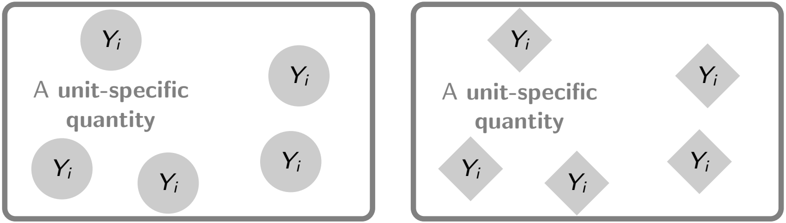

Averaged over a **target population** of **mothers**

Averaged over a **target population** of **non-mothers**

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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"causal estimation techniques"

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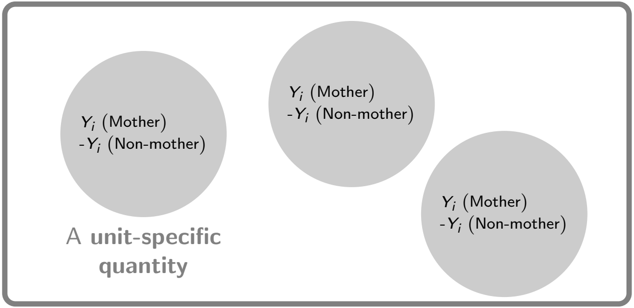
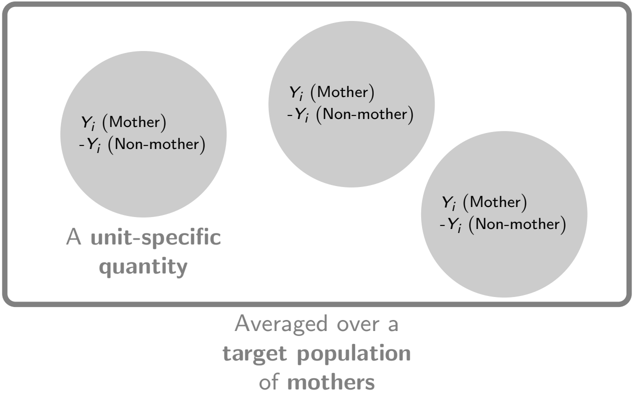


Averaged over a **target population** of **mothers**

Pal and Waldfogel (2016) estimate the family gap in pay.

Is the theoretical estimand descriptive? Is it causal?

Added complexity: Wages are undefined for the non-employed.



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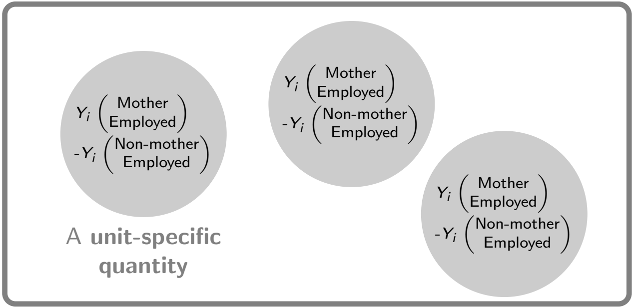

Averaged over a **target population** of **mothers**

Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\\text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\\text{Employed}\end{pmatrix}$

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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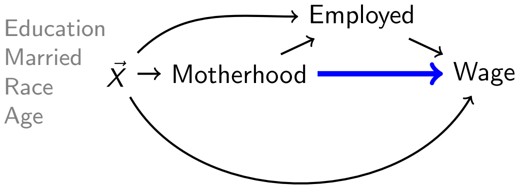
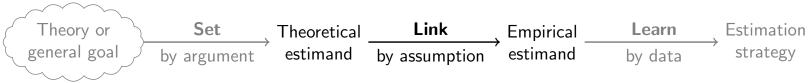
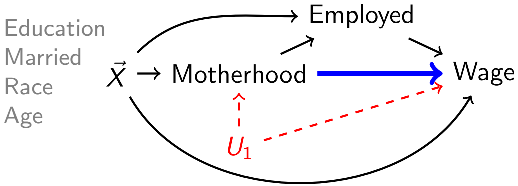


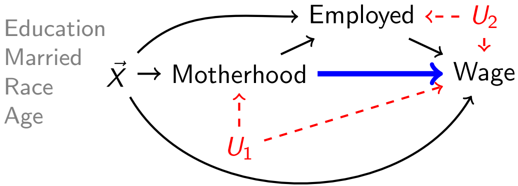


Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\ \text{Employed}\end{pmatrix}$



Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\\text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\\text{Employed}\end{pmatrix}$



Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\ \text{Employed}\end{pmatrix}$

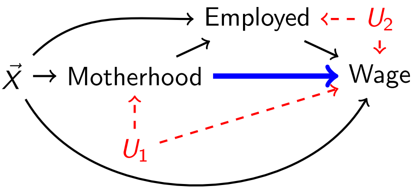
Potential outcomes

$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

All women
with a high school degree,
married, white, age 30

Focus on
one $\vec{X} = \vec{x}_i$

Education
Married
Race
Age



Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

$$\mathrm{E}\left(Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}\,\middle|\,\vec{X}=\vec{x}_i\right)$$

Potential outcomes

$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

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Married
Race
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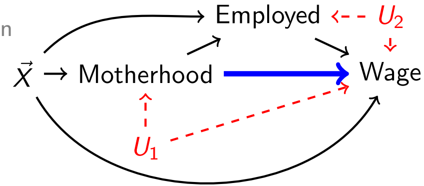

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

$$\mathrm{E}\left(Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}\middle|\,\vec{X}=\vec{x}_i\right)$$

Potential outcomes

$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

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with a high school degree,
married, white, age 30

Focus on
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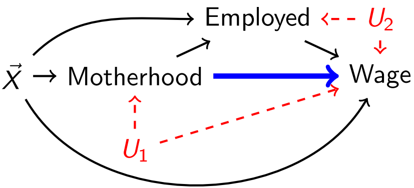
Education
Married
Race
Age



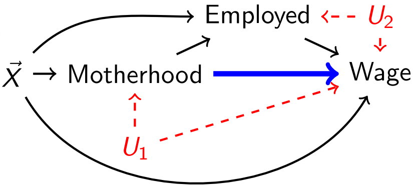
Theory or general goal —**Set** by argument→ Theoretical estimand —**Link** by assumption→ Empirical estimand —**Learn** by data→ Estimation strategy

$$\mathrm{E}\left(Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)\,\middle|\,\vec{X}=\vec{x}_i\right) \quad ? \quad \mathrm{E}\left(Y_i\,\middle|\,\begin{matrix}\text{Motherhood} & = & \text{Mother,}\\ \text{Employment} & = & \text{Employed,}\\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i\end{matrix}\right)$$

Potential outcomes	**Realized** outcomes
$Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$ $Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$ $Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$	Y_i Y_i
All women with a high school degree, married, white, age 30	**Employed mothers** with a high school degree, married, white, age 30

Focus on one $\vec{X}=\vec{x}_i$

Education
Married
Race
Age



Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

$$\mathrm{E}\left(Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix} \middle| \vec{X}=\vec{x}_i\right) \underset{\text{By the DAG}}{=} \mathrm{E}\left(Y_i \middle| \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,}\\ \text{Employment} & = & \text{Employed,}\\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i\end{array}\right)$$

Potential outcomes

$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

All women
with a high school degree,
married, white, age 30

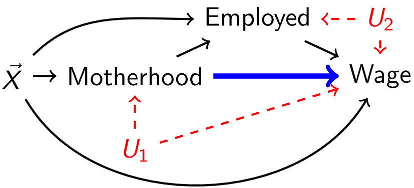
Realized outcomes

Y_i Y_i

Employed mothers
with a high school degree,
married, white, age 30

Focus on one $\vec{X}=\vec{x}_i$

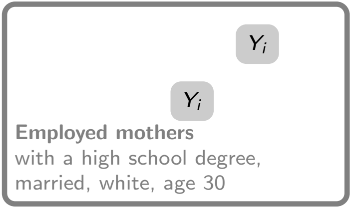
Education
Married
Race
Age



Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

$$\mathrm{E}\left(Y_i \,\middle|\, \begin{array}{ccc} \text{Motherhood} & = & \text{Mother}, \\ \text{Employment} & = & \text{Employed}, \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Realized outcomes



Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

This can be estimated by **machine learning**!

$$\text{E}\left(Y_i \;\middle|\; \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,} \\ \text{Employment} & = & \text{Employed,} \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Realized outcomes

Y_i

Y_i

Employed mothers
with a high school degree,
married, white, age 30

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

This can be estimated by **machine learning**! $\longrightarrow$

$$\text{E}\left(Y_i \,\middle|\, \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,} \\ \text{Employment} & = & \text{Employed,} \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Any prediction algorithm that minimizes squared errors

Realized outcomes

Y_i

Y_i

Employed mothers
with a high school degree, married, white, age 30

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

This can be estimated by **machine learning**! $\longrightarrow$

$$\mathrm{E}\left(Y_i \;\middle|\; \begin{array}{lcr} \text{Motherhood} & = & \text{Mother}, \\ \text{Employment} & = & \text{Employed}, \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

$\downarrow$

Any prediction algorithm that minimizes squared errors

$\downarrow$

Generalized Additive Model

Realized outcomes

Y_i

Y_i

Employed mothers
with a high school degree, married, white, age 30

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

This can be estimated by **machine learning**!

$$\mathrm{E}\left(Y_i \,\middle|\, \begin{array}{lcr} \text{Motherhood} & = & \text{Mother}, \\ \text{Employment} & = & \text{Employed}, \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Any prediction algorithm that minimizes squared errors

Generalized Additive Model

Random Forest

Realized outcomes

Y_i

Y_i

Employed mothers
with a high school degree, married, white, age 30

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

This can be estimated by **machine learning**!

$$\text{E}\left(Y_i \;\middle|\; \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,} \\ \text{Employment} & = & \text{Employed,} \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Any prediction algorithm that minimizes squared errors

Ordinary Least Squares

Generalized Additive Model

Random Forest

Realized outcomes

Y_i

Y_i

Employed mothers
with a high school degree,
married, white, age 30

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Mechanics: How **predictive algorithms** estimate the **estimand**

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{\text{E}}\left(Y_i \middle| \begin{array}{rcl} \text{Motherhood} & = & \texttt{Mother}, \\ \text{Employment} & = & \texttt{Employed}, \\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i \end{array}\right)$$

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{Y}_i\begin{pmatrix}\texttt{Mother,}\\ \texttt{Employed}\end{pmatrix} = \hat{\text{E}}\left(Y_i \middle| \begin{array}{lcr}\text{Motherhood} & = & \texttt{Mother,}\\ \text{Employment} & = & \texttt{Employed,}\\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i\end{array}\right)$$

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{Y}_i\begin{pmatrix}\texttt{Non-mother},\\ \texttt{Employed}\end{pmatrix} = \hat{\text{E}}\left(Y_i \,\middle|\, \begin{array}{rcl}\text{Motherhood} & = & \texttt{Non-mother},\\ \text{Employment} & = & \texttt{Employed},\\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i\end{array}\right)$$

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{Y}_i\begin{pmatrix}\texttt{Non-mother,}\\ \texttt{Employed}\end{pmatrix} = \hat{\text{E}}\left(Y_i \,\middle|\, \begin{array}{rcl}\text{Motherhood} & = & \texttt{Non-mother,}\\ \text{Employment} & = & \texttt{Employed,}\\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i\end{array}\right)$$

$$\hat{Y}_i\begin{pmatrix}\texttt{Mother,}\\ \texttt{Employed}\end{pmatrix} - \hat{Y}_i\begin{pmatrix}\texttt{Non-mother,}\\ \texttt{Employed}\end{pmatrix}$$

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{Y}_i\begin{pmatrix}\texttt{Non-mother},\\ \texttt{Employed}\end{pmatrix} = \hat{\text{E}}\left(Y_i \,\middle|\, \begin{array}{lcc}\text{Motherhood} & = & \texttt{Non-mother},\\ \text{Employment} & = & \texttt{Employed},\\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i\end{array}\right)$$

3) Average over the target population

$$\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i\begin{pmatrix}\texttt{Mother},\\ \texttt{Employed}\end{pmatrix} - \hat{Y}_i\begin{pmatrix}\texttt{Non-mother},\\ \texttt{Employed}\end{pmatrix}\right)$$

Mechanics: How **predictive algorithms** estimate the **estimand**

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

$$\hat{Y}_i\begin{pmatrix}\texttt{Non-mother,}\\ \texttt{Employed}\end{pmatrix} = \hat{\mathrm{E}}\left(Y_i \,\middle|\, \begin{array}{rcl}\text{Motherhood} & = & \texttt{Non-mother,}\\ \text{Employment} & = & \texttt{Employed,}\\ \text{Covariates } \vec{X} & = & \texttt{Observed } \vec{x}_i\end{array}\right)$$

3) Average over the target population

$$\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i\begin{pmatrix}\texttt{Mother,}\\ \texttt{Employed}\end{pmatrix} - \hat{Y}_i\begin{pmatrix}\texttt{Non-mother,}\\ \texttt{Employed}\end{pmatrix}\right)$$

This is called an **imputation estimator**

Hahn, 1998

Abadie & Imbens 2006

Also called the parametric g-formula in biostatistics, Hernán & Robins 2020

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Choose an algorithm by **predictive performance**

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Candidate algorithms

Least flexible

Most flexible

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Least flexible OLS with a quadratic for age

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Least flexible OLS with a quadratic for age

+ Interaction between age and motherhood

Most flexible

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

Least flexible	OLS with a quadratic for age
	+ Interaction between age and motherhood
	+ Allow a smooth curve for age rather than quadratic
Most flexible	

Choose an algorithm by **predictive performance**

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Predictors Motherhood, age, race, education, marital status

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- OLS with a quadratic for age
- + Interaction between age and motherhood
- + Allow a smooth curve for age rather than quadratic
- + Include each age as a separate indicator variable

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Choices about **functional form**

Choose an algorithm by **predictive performance**

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Least flexible	OLS with a quadratic for age
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Choose an algorithm by **predictive performance**

Outcome Log hourly wage

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Candidate algorithms

Least flexible	OLS with a quadratic for age
	+ Interaction between age and motherhood
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Our framework partitions research choices

Some choices must be **theory-driven**

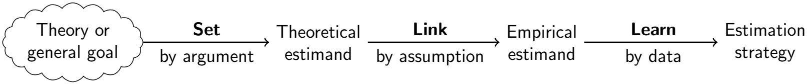
— What question is important? — theoretical estimand

— What variables should I adjust? — empirical estimand

Some choices can be **data-driven**

— Do I include a squared term? — estimation strategy

— Do I need an interaction?



Replication 2

Coefficient-based reasoning hampers understanding

	β	(SE)
Birth Cohort 1966+ (vs. 1938–1965)	.318	(.285)
Female	–.136	(.133)
Later Cohorts × Female	–.107	(.272)
Mother Some College	.737**	(.134)
Later Cohorts × Mother Some College	.079	(.218)
No Father Present	–.031	(.129)
Father Some College	1.285**	(.113)
Later Cohorts × No Father	–.107	(.226)
Later Cohorts × Father Some College	–.390	(.211)
Mother Some College × Female	.120	(.147)
No Father Present × Female		
Father Some College × Female		
Mother Some College × No Father	.108	(.208)
Mother Some College × Father Some College	.150	(.138)
No Father or Father ≤HS × Male	.303*	(.143)
No Father or Father ≤HS × Male × Later Cohorts	–.801**	(.293)
Mother Some College × Female × Later Cohorts	.221	(.295)
No Father × Female × Later Cohorts		
Father Some College × Male × Later Cohorts		
Age Main Effects	(omitted)	
2- and 3-way Interactions between Age and (Gender, Cohort)	(omitted)	
Constant	1.695**	(.140)
N	7,024	
df	15	

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Coefficient:
Gender $\times$ Cohort
$\times$ Father status

> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
>
> — Buchmann and DiPrete 2006

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Coefficient:
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Descriptive estimand: Proportion completing college within subgroups of the predictors

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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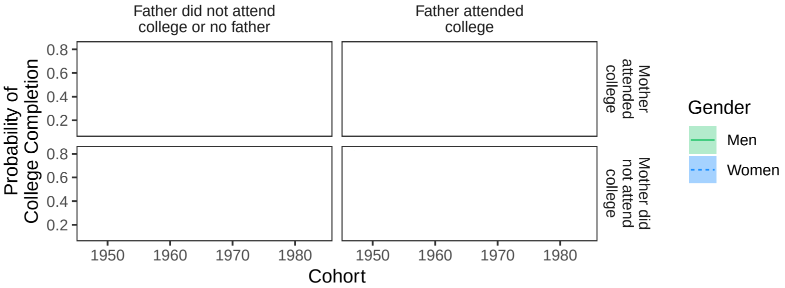

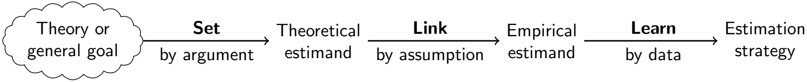

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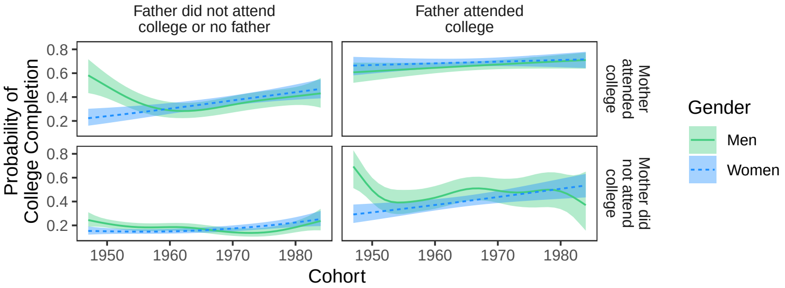

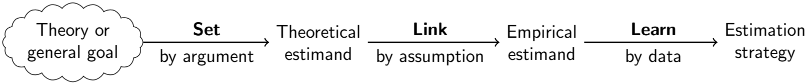

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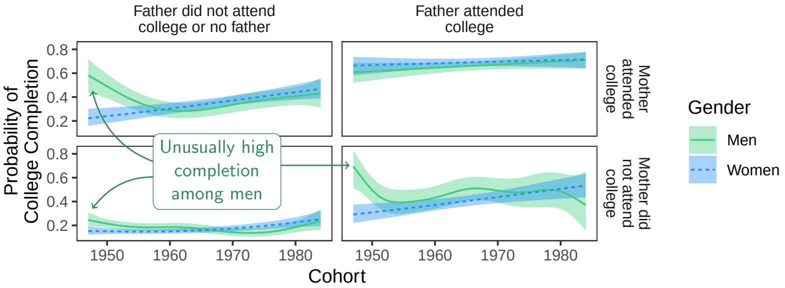

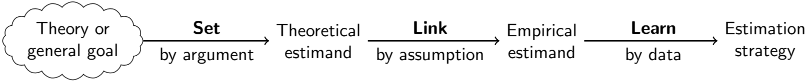

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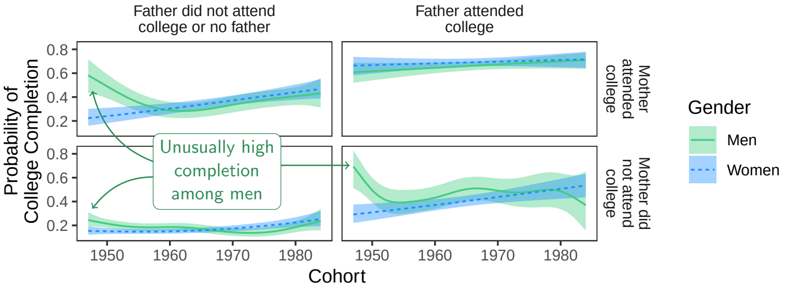
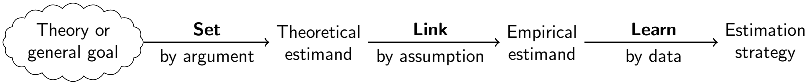


Alternate theory: The Vietnam War



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

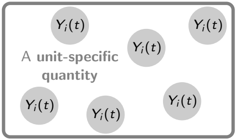
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

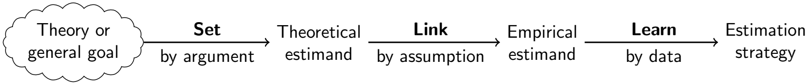
→ **Replicate** studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



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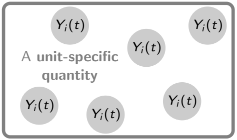

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The Gap-Closing Estimand:
A Causal Approach to Study Interventions
That Close Disparities Across Social Categories

Lundberg, Ian
Working paper
On SocArxiv

Standard practice: Report the coefficient on race, gender, or class.

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But is "treatment" the right role for these complex constructs?

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Question we ask $\xleftarrow{\textbf{constrain}}$ Familiar methods

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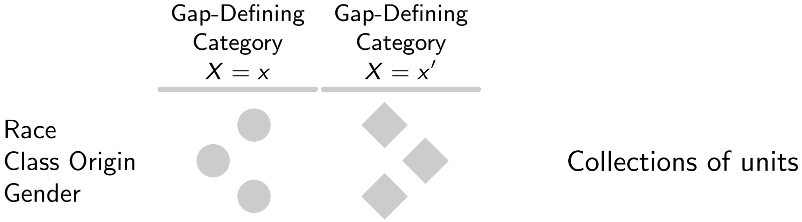
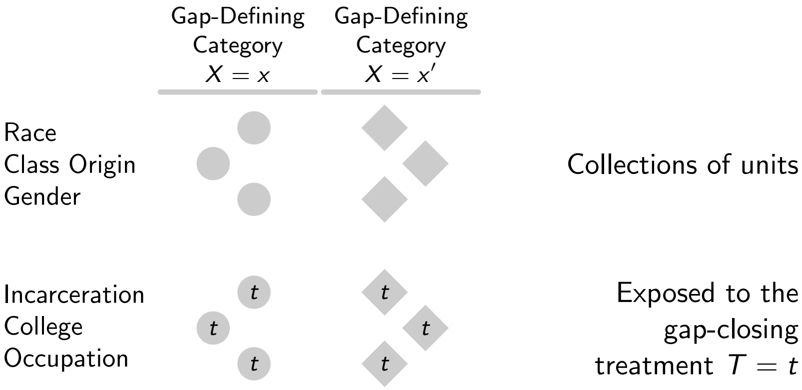
Question we ask $\xleftarrow{\text{constrain}}$ Familiar methods

Theoretical questions $\xrightarrow{\text{motivate}}$ Things we do to data


Gap-Defining Category $X = x$
Gap-Defining Category $X = x'$
Race
Class Origin
Gender
Collections of units



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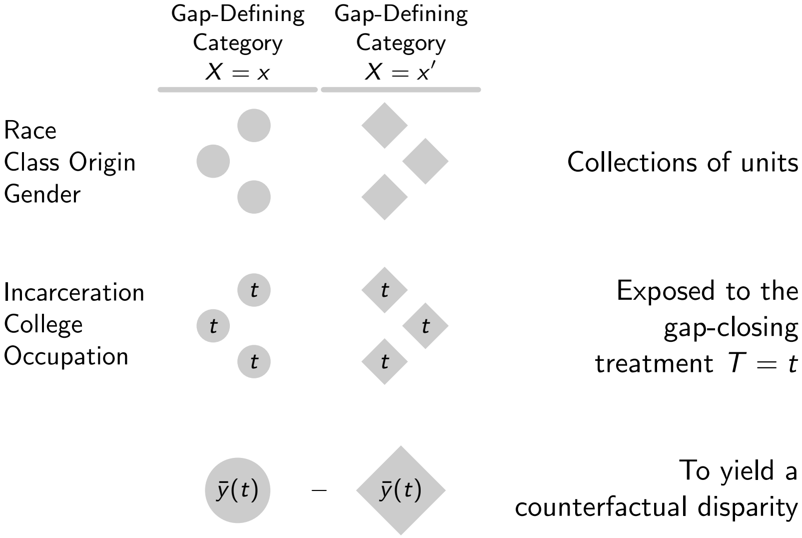

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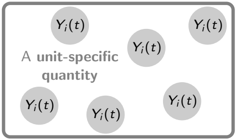

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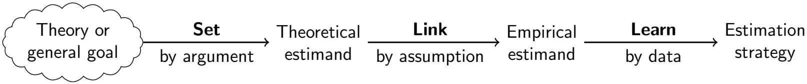

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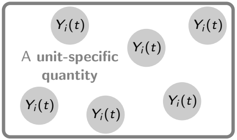

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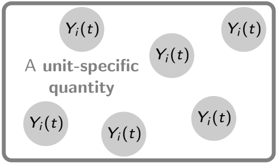

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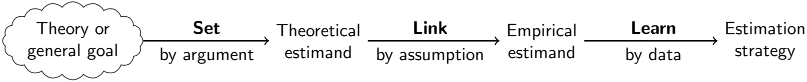

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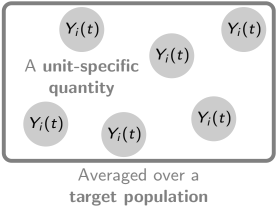
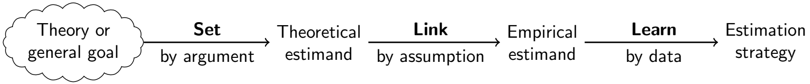
When you **write** a quantitative paper, the estimand allows you to





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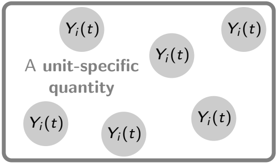
— Motivate the question outside the model



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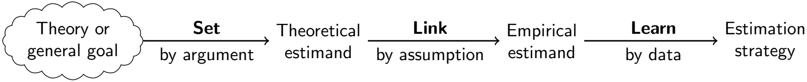

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When you **write** a quantitative paper, the estimand allows you to

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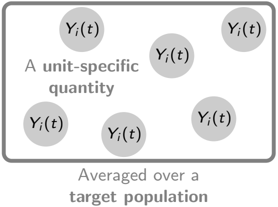
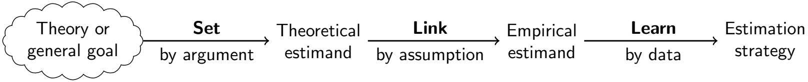
— Address selection transparently





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When you **write** a quantitative paper, the estimand allows you to

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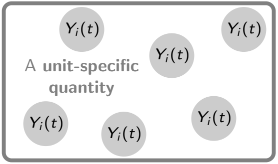
— Unlock computational tools



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When you **write** a quantitative paper, the estimand allows you to

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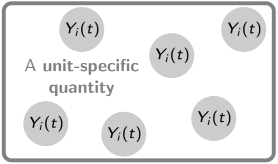
— Unlock computational tools

— Present interpretable summaries



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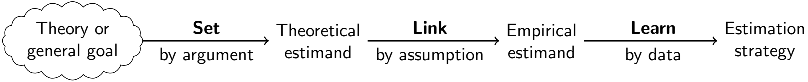
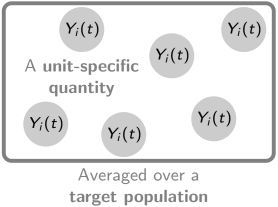


What is your estimand? ⟵ Every quantitative study should answer this question

When you **read** a quantitative paper, the estimand allows you to

— Understand the author’s aim

— Pinpoint your concerns



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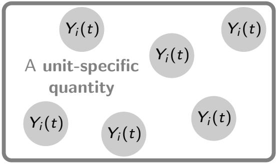
In the future, estimands will only become more important



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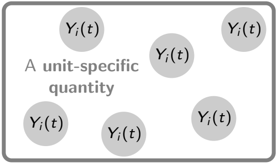
New data have missing values

— Non-probability samples

— Administrative records



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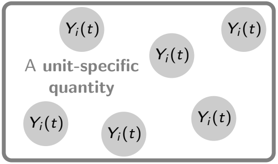
New methods flourish with a clear goal

— Machine learning



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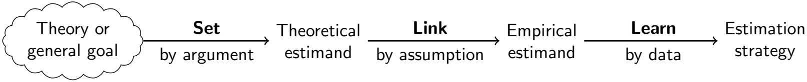


What is your estimand?

⟵ Every quantitative study should answer this question

In the future, estimands will only become more important

New data have missing values

— Non-probability samples

— Administrative records

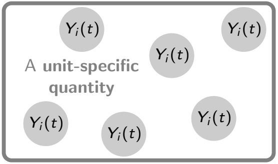
New methods flourish with a clear goal

— Machine learning

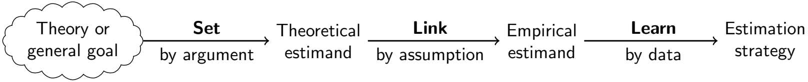
New questions can be found beyond coefficients

— Describe counterfactual disparities

— Predict the effects of targeted interventions



Averaged over a **target population**



What is your estimand?

⟵ Every quantitative study should answer this question

Defining the Target Quantity Connects Statistical Evidence to Theory

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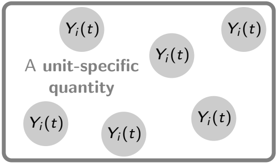

Averaged over a **target population**

Paper in *American Sociological Review*
Open Access on SocArxiv
Code on Dataverse

Learning goals for today

At the end of class, you will be able to:

1. Connect key concepts from this class to issues in social science today
2. Be ready to apply those concepts in your research proposal

Let me know what you are thinking

tinyurl.com/CausalQuestions

Office hours TTh 11am-12pm and at
calendly.com/ianlundberg/office-hours
Come say hi!