

What is Your Estimand?

Defining the Target Quantity
Connects Statistical Evidence
to Theory



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**Epistemological
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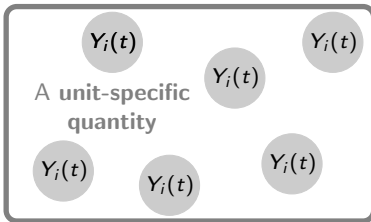
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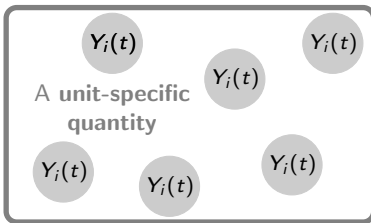
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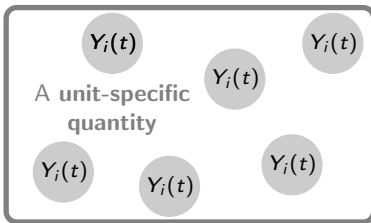


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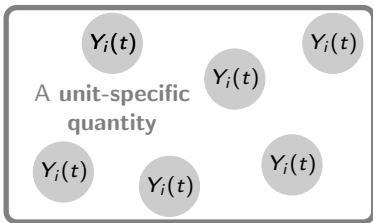


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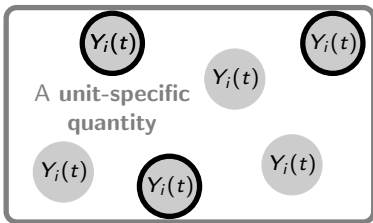


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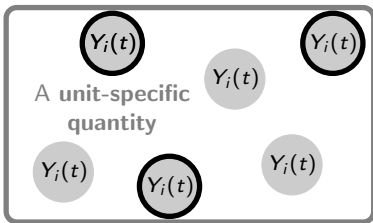


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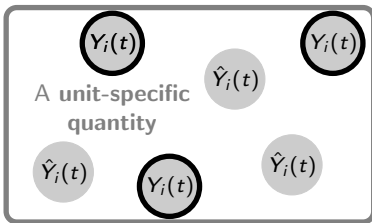


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Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

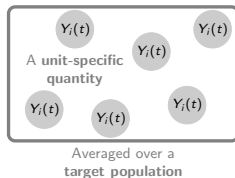
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Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand





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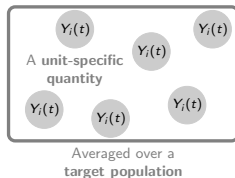
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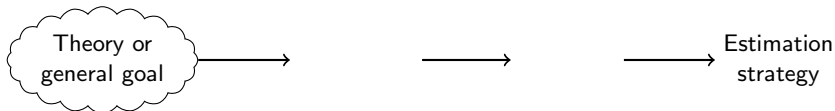
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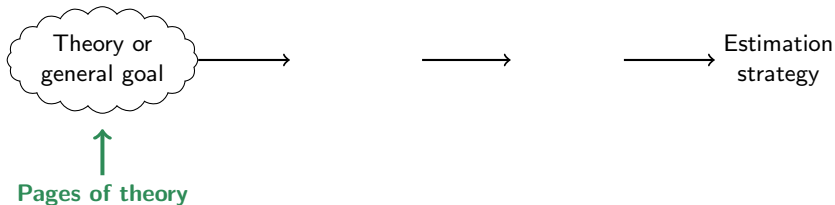
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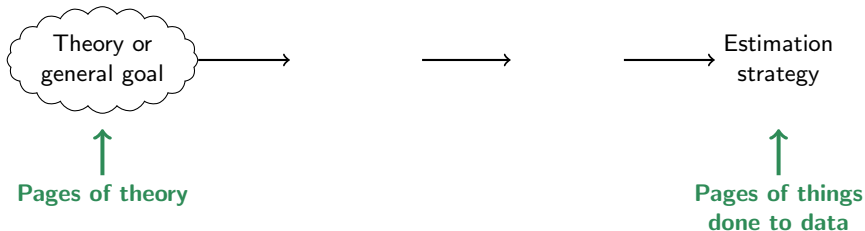
Research framework: Estimands connect theory to evidence



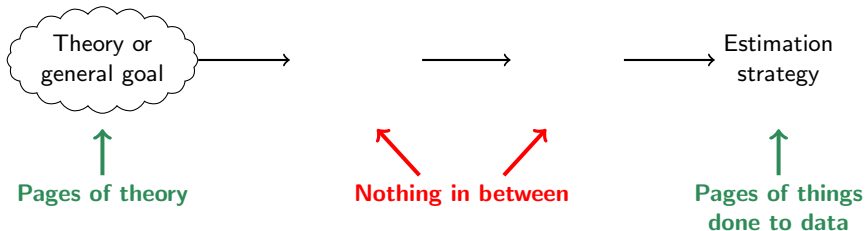
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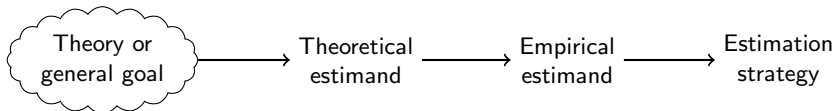
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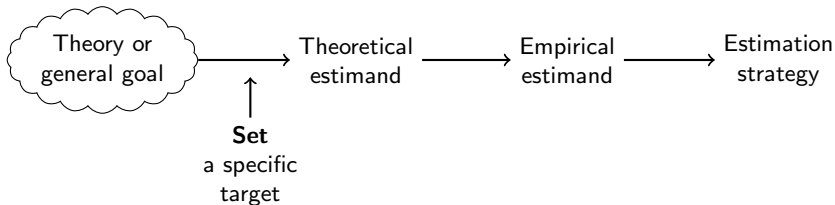
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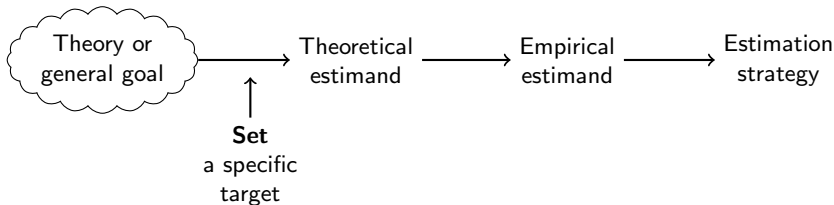
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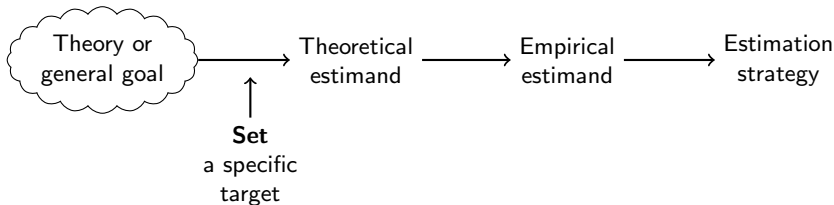
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Definition

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

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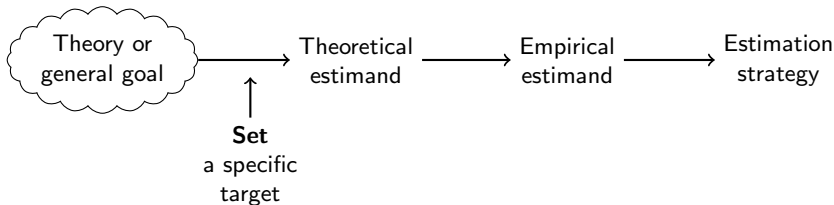
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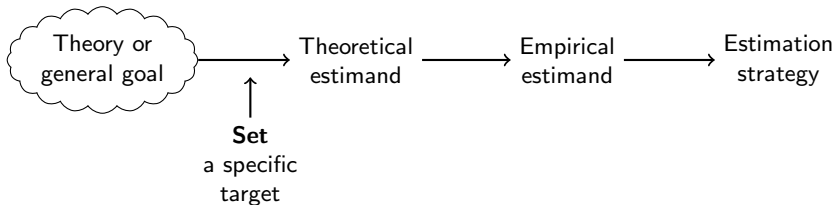
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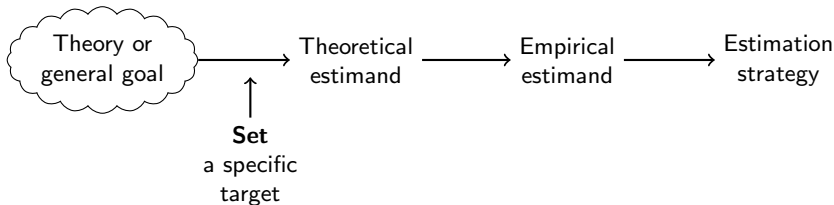
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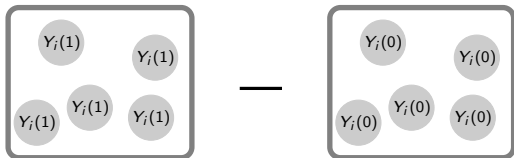
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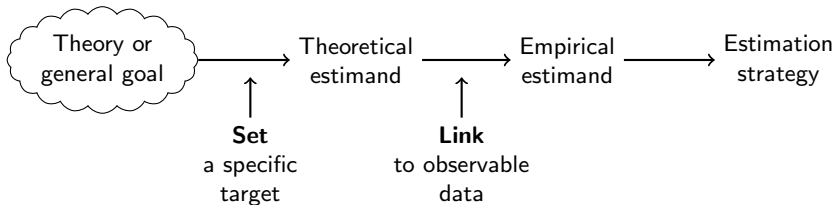
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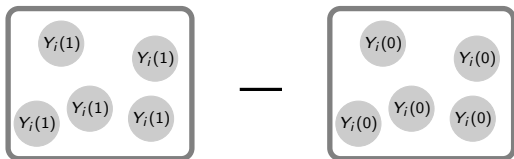
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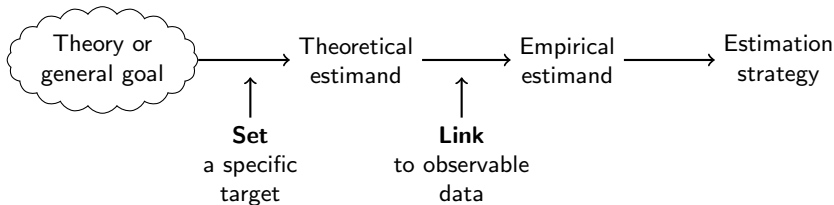
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A quantity involving
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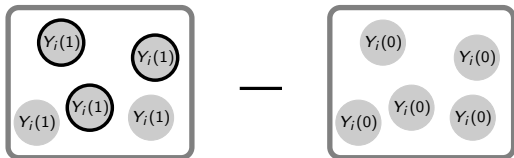
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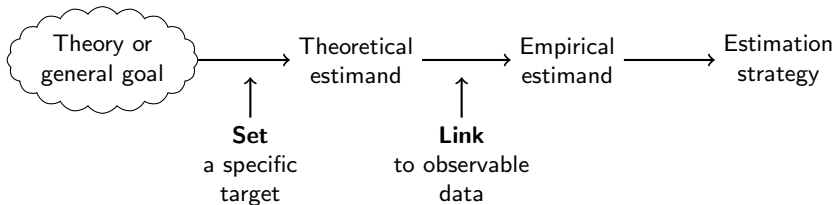
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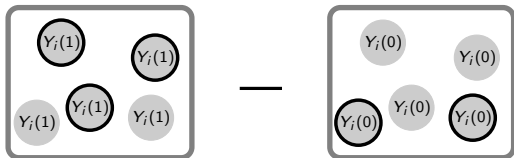
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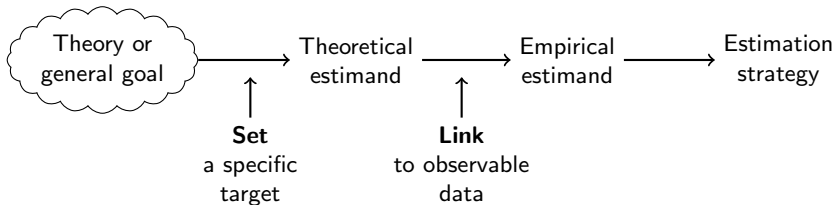
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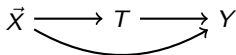
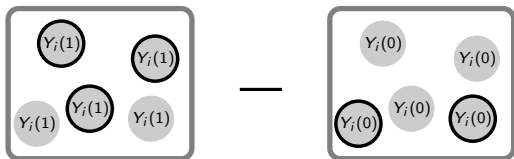
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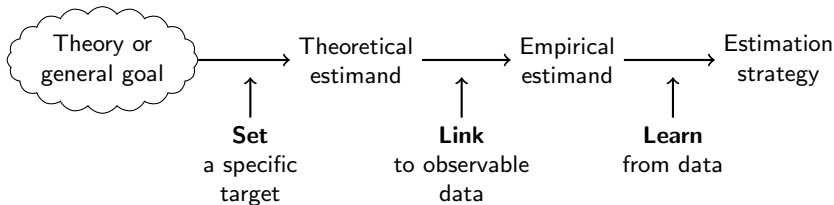
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Pearl 2009, Imbens and Rubin 2015,
Morgan and Winship 2015, Elwert and Winship 2014

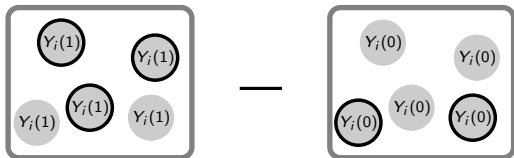
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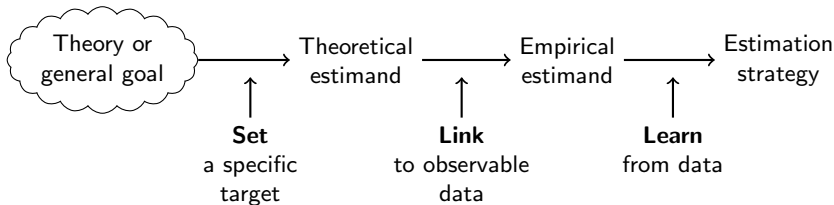
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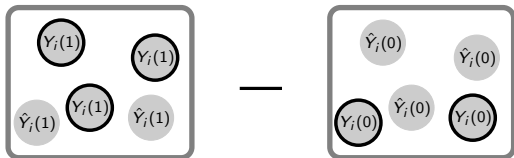
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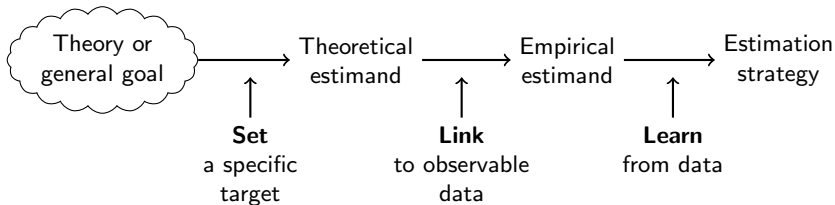
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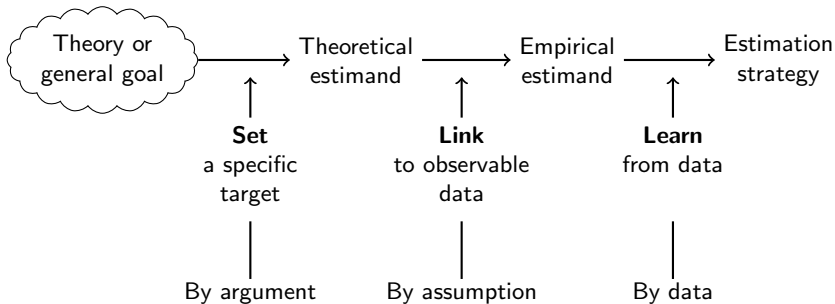


Young 2009, Watts 2014, Berk et al. 2019, Molina and Garip 2019

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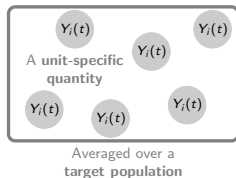
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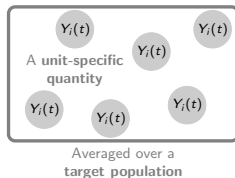
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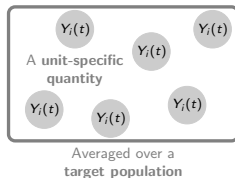
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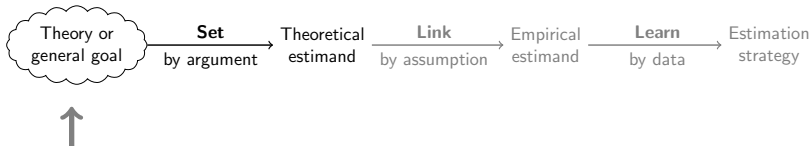
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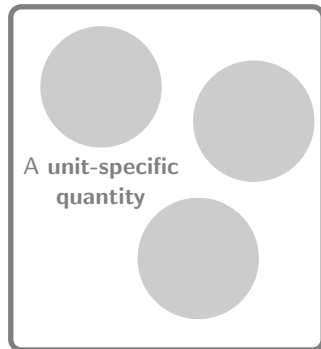
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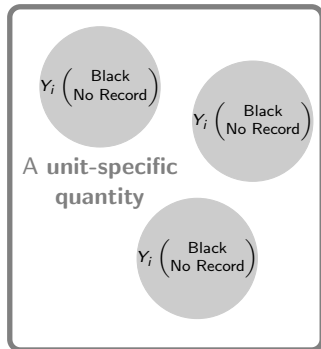


Averaged over a
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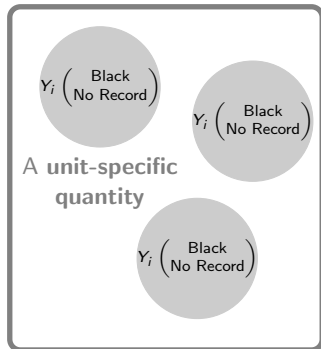


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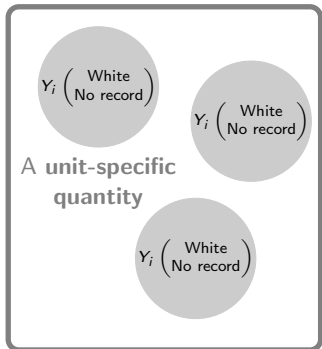
Key insight:

Each unit i is an application,
not a person.

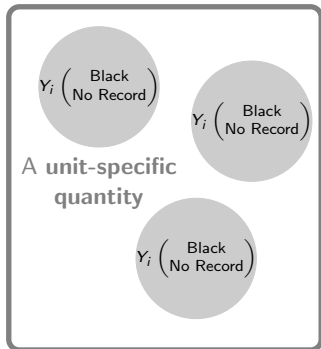


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Greiner & Rubin 2011, Sen & Wasow 2016, Kohler-Hausmann 2018



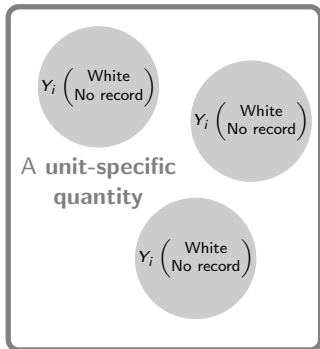
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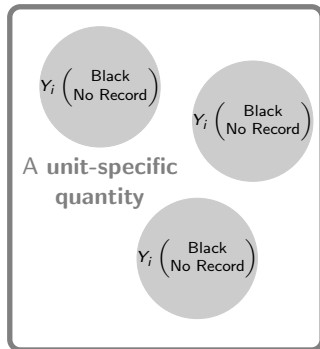
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Discrimination: One population of applications



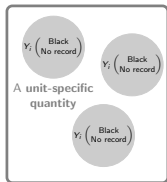
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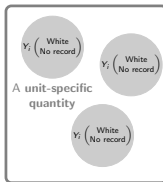
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Estimand 1: Racial **discrimination**



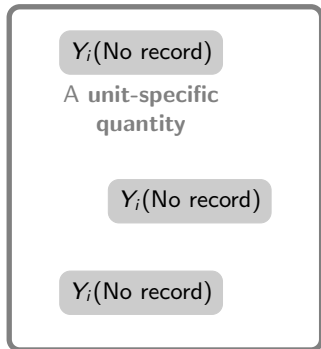
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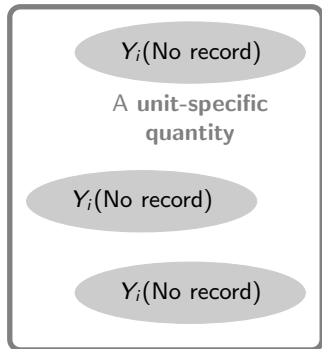
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Estimand 2: Racial **disparity** under ban-the-box



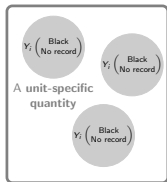
Averaged over
black applicants



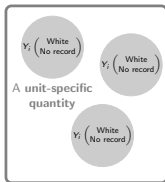
Averaged over
white applicants



Estimand 1: Racial **discrimination**

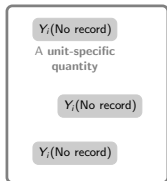


Averaged over all applications

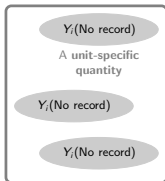


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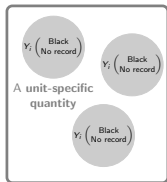
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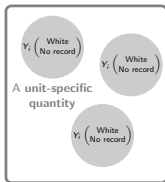
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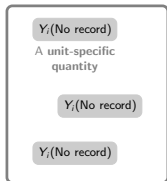
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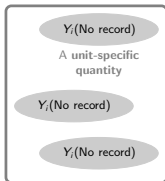
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Two treatment
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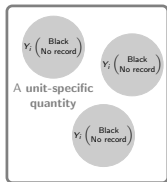
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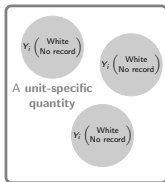
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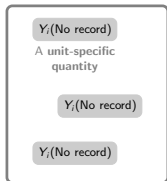


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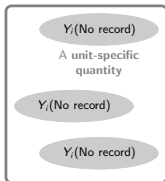
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What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

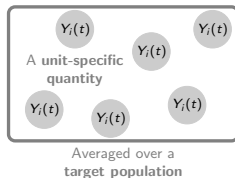
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Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand





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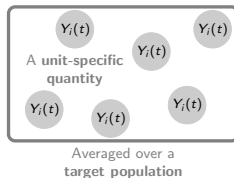
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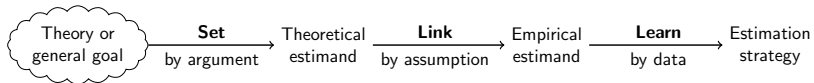
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Angrist and Evans 1998



Effect of motherhood
on employment

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Effect of motherhood
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First two births
are the same sex

Angrist and Evans 1998



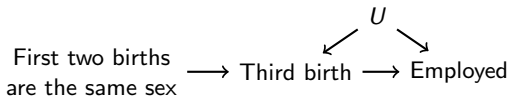
Effect of motherhood
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First two births are the same sex \longrightarrow Third birth

Angrist and Evans 1998



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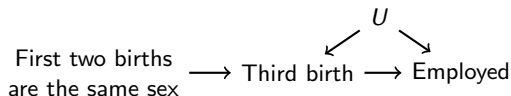


Angrist and Evans 1998



Vague estimand

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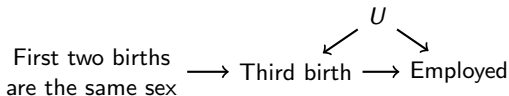
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Vague estimand

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Precise estimand



Angrist and Evans 1998



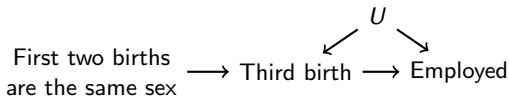
Vague estimand

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Precise estimand

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

**unit-specific
quantity**



Angrist and Evans 1998



Vague estimand

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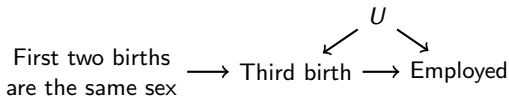
target population



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



Angrist and Evans 1998



Precise estimand

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$\approx 4\%$ of all mothers

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You have to argue either:

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Angrist and Evans 1998



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You have to argue either:

- 1) That estimand matters for theory, or
- 2) It speaks to some broader estimand

Angrist and Evans 1998



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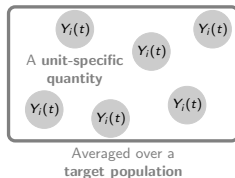
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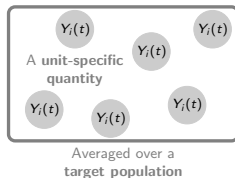
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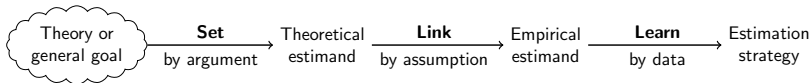
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Example: Age-standardized mortality



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Descriptive Estimand

Causal Estimand



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Descriptive Estimand

Age-specific mortality
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Causal Estimand



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A “counterfactual” population

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Meaningful 



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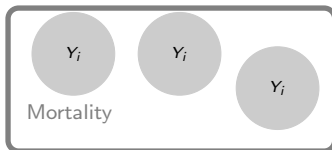
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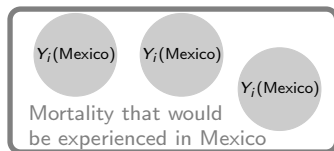
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Averaged over
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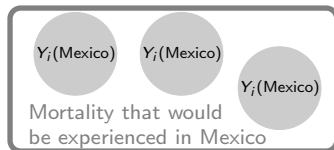
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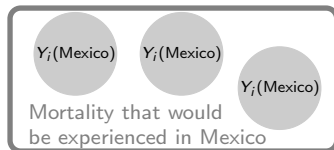
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This same issue applies to
all sociological studies
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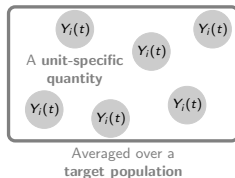
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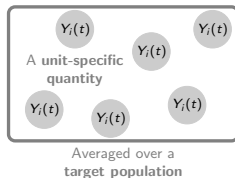
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An Empirical Analysis of Racial Differences in Police Use of Force

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)

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TheUpshot
DATA DIVE

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



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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)

1. Introduction

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

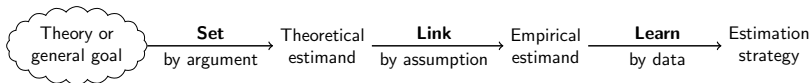
This work has benefited greatly from discussions and debate with Chief William Evans, Chief Charles McClelland, Chief Martha Montalvo, Sergeant Stephen Morrison, Jon Murad, Lynn Overmann, Chief Rod Riley, and Chief Scott Thompson. I am grateful to David Card, Kevin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Omerlock, Jesse Shapiro, Andrei Shleifer, Jorg Spengler, Max Stoss, John Van Buren, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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It is the most surprising result of my career.
— Roland Fryer



Reality check: study finds no racial bias in police shootings
The Guardian

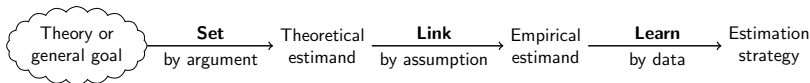


Evidence:

Claim:

Why wrong:

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

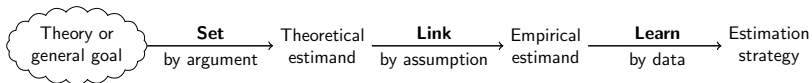


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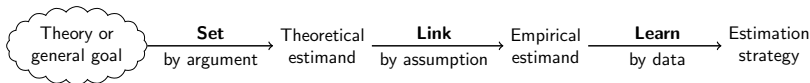
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Lundberg, Johnson, and Stewart. What is Your Estimand?



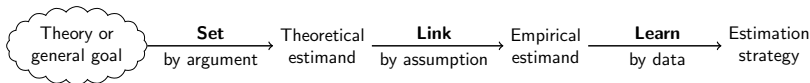
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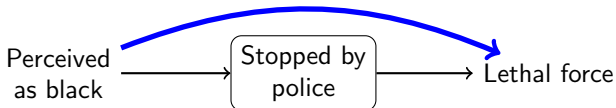
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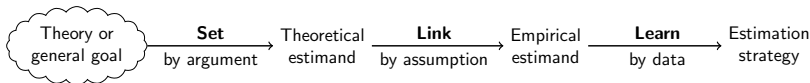
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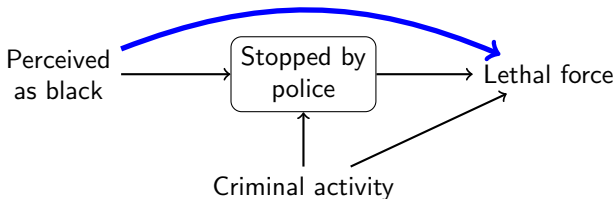
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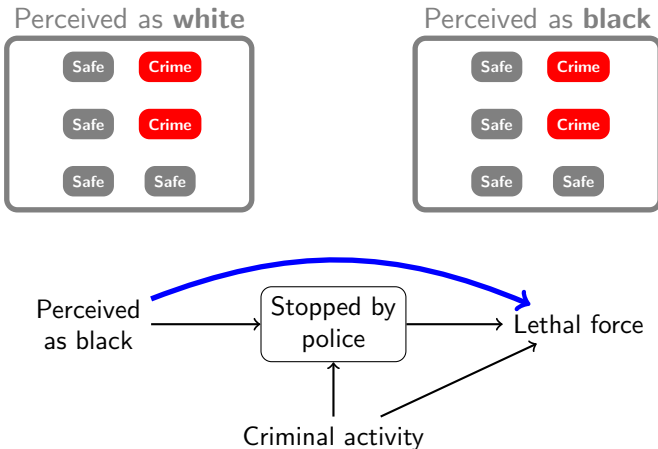
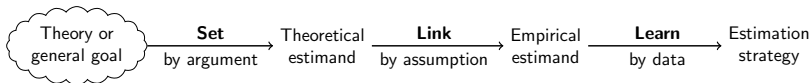
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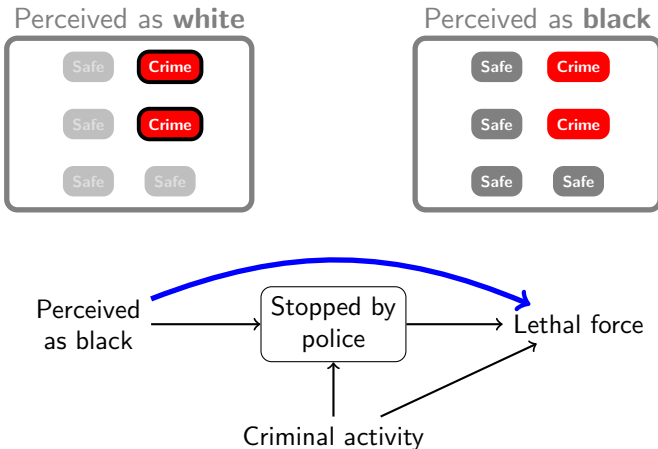
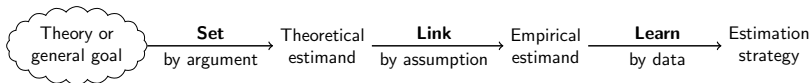
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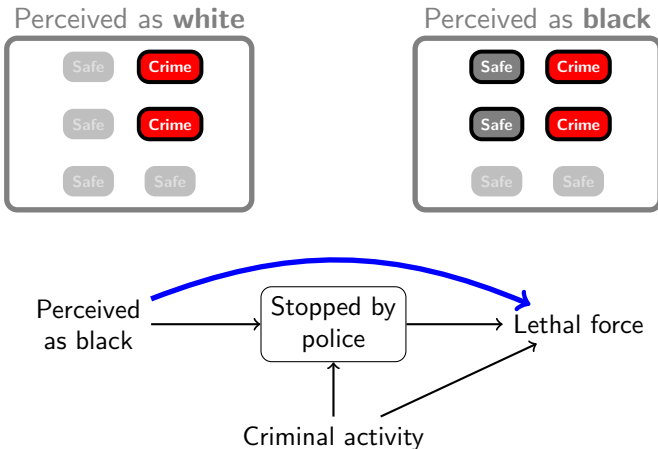
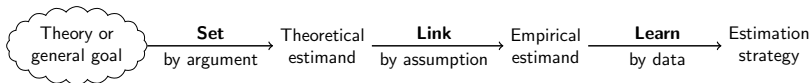
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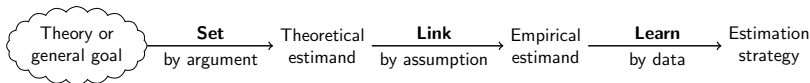
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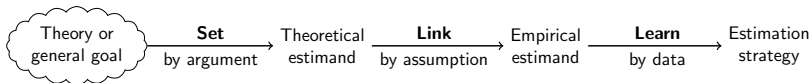


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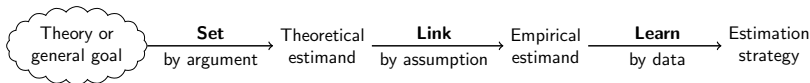
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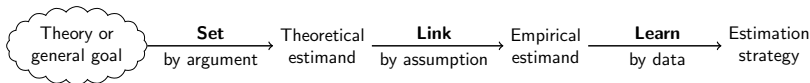
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Fryer responds:

“We use the term ‘racial differences’ 114 times in lieu of the more prescriptive wording—‘racial discrimination.’ We use the phrase ‘conditional on an interaction’ 20 times...I am not sure how many more ways we would have needed to caveat our results to satisfy [the critics].”

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



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:

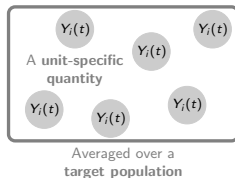
- 1) Distinguish causal treatments from population labels
- 2) Recognize when empirical evidence is narrow
- 3) Address ambiguity about descriptive and causal claims
- 4) Beware of causal selection in descriptive claims

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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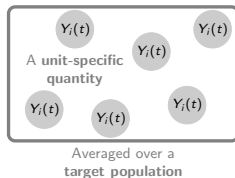
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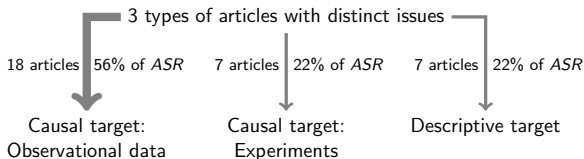
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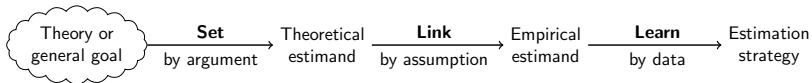


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Clarity about **unit-specific quantity**

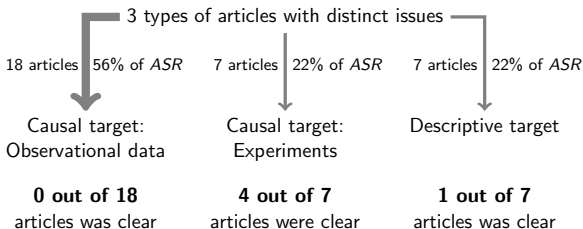




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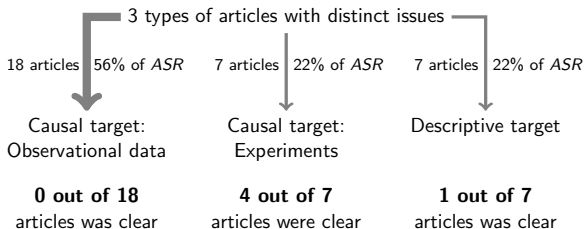




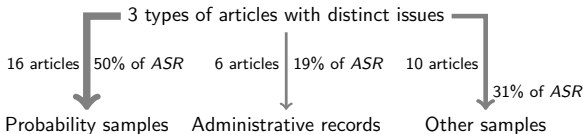
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Clarity about **unit-specific quantity**



Clarity about the **target population**

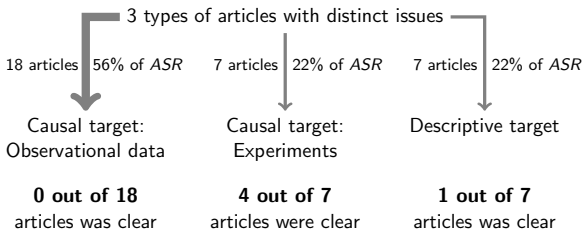




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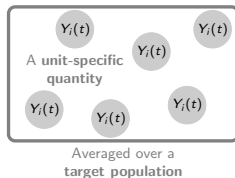
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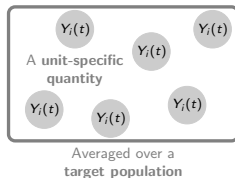
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Replication 1

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



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



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Is the theoretical estimand descriptive?



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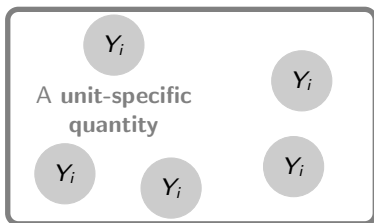
“the differential in hourly wages
between women with children
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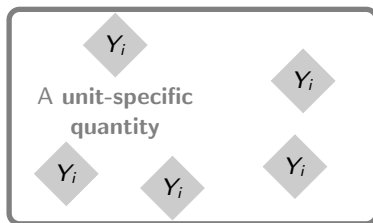
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Averaged over a
target population
of **mothers**



Averaged over a
target population
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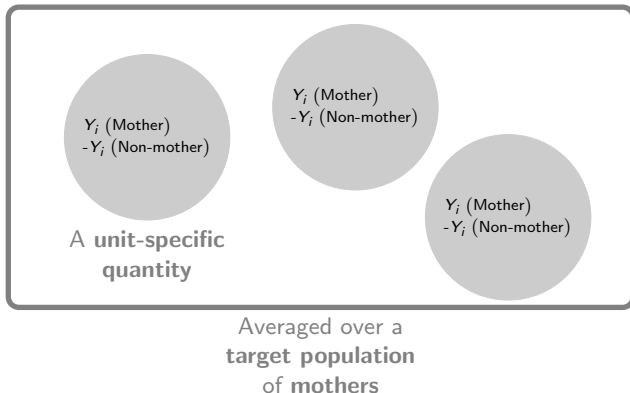
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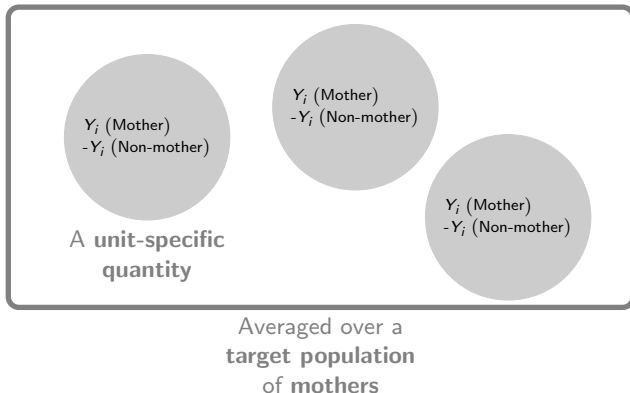




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Added complexity: Wages are undefined for the non-employed.

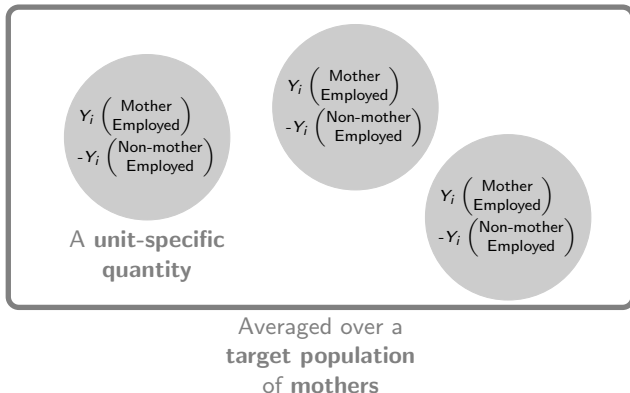


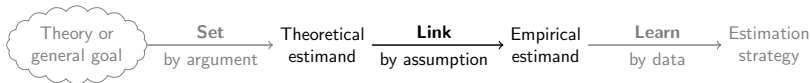


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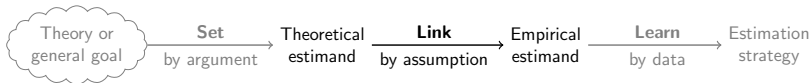
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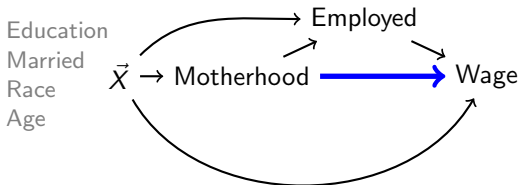


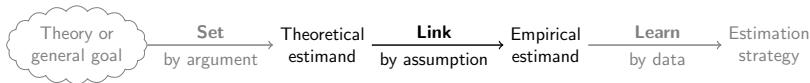


Unit-specific quantity: $Y_i \left(\begin{array}{c} \text{Mother,} \\ \text{Employed} \end{array} \right) - Y_i \left(\begin{array}{c} \text{Non-mother,} \\ \text{Employed} \end{array} \right)$

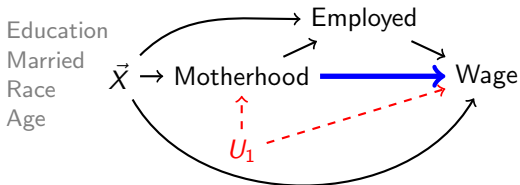


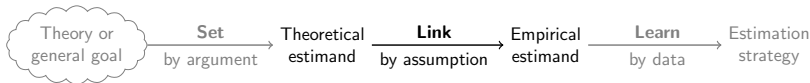
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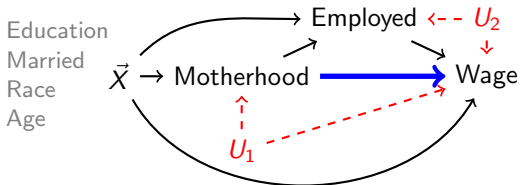


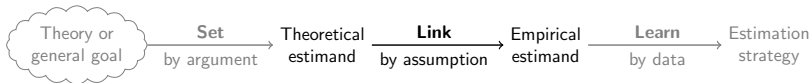
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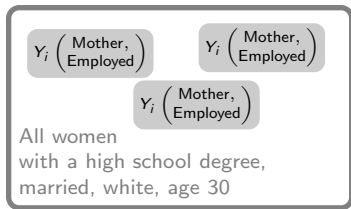
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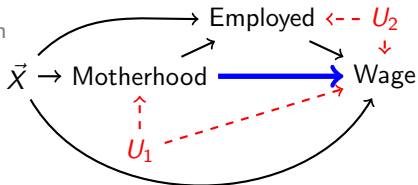
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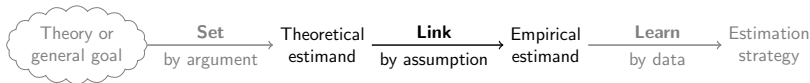
Potential outcomes



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

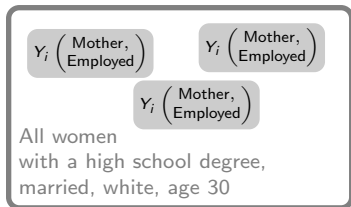
Education
Married
Race
Age





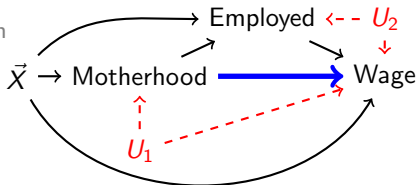
$$E \left(Y_i \left(\begin{matrix} \text{Mother,} \\ \text{Employed} \end{matrix} \right) \mid \vec{X} = \vec{x}_i \right)$$

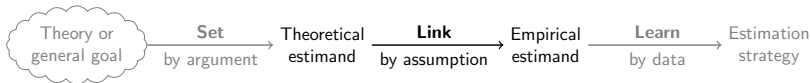
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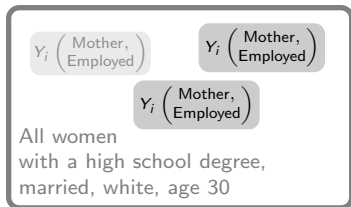
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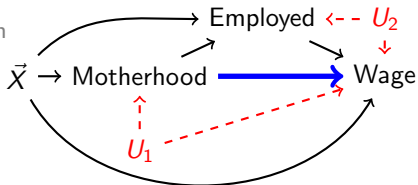
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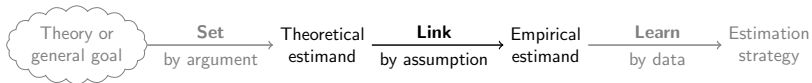
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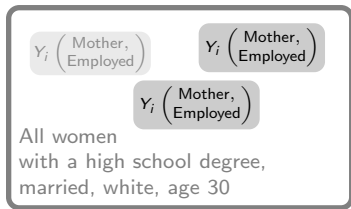
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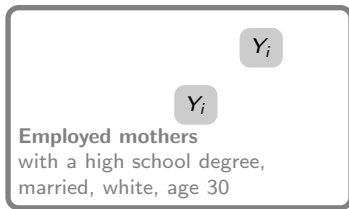


$$E \left(Y_i \left(\begin{matrix} \text{Mother,} \\ \text{Employed} \end{matrix} \right) \middle| \vec{X} = \vec{x}_i \right) \quad ? \quad E \left(Y_i \middle| \begin{matrix} \text{Motherhood} = \text{Mother,} \\ \text{Employment} = \text{Employed,} \\ \text{Covariates } \vec{X} = \text{Observed }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

Potential outcomes

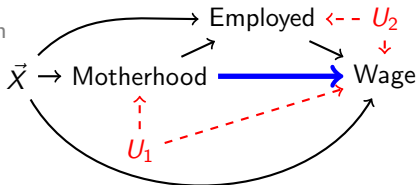


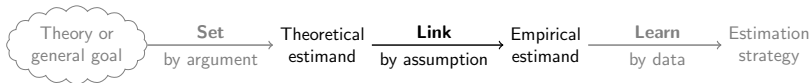
Realized outcomes



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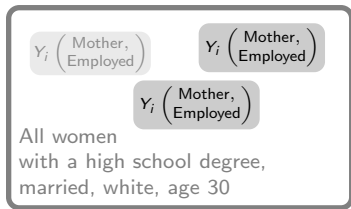




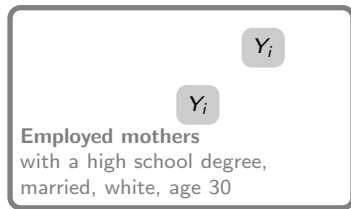
$$E \left(Y_i \left(\begin{matrix} \text{Mother,} \\ \text{Employed} \end{matrix} \right) \mid \vec{X} = \vec{x}_i \right) = E \left(Y_i \mid \begin{matrix} \text{Motherhood} = \text{Mother,} \\ \text{Employment} = \text{Employed,} \\ \text{Covariates } \vec{X} = \text{Observed } \vec{x}_i \end{matrix} \right)$$

By the DAG

Potential outcomes

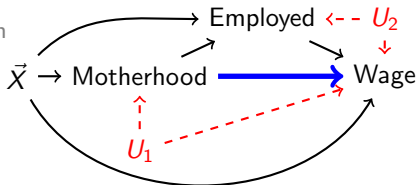


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Focus on
one $\vec{X} = \vec{x}_i$

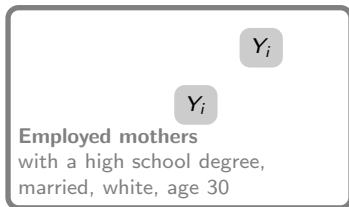
Education
Married
Race
Age





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

Realized outcomes

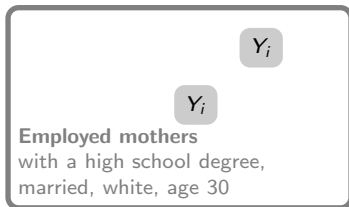




This can be estimated
by machine learning!

$$\longrightarrow E \left(Y_i \mid \begin{array}{l} \text{Motherhood} \\ \text{Employment} \\ \text{Covariates } \vec{X} \end{array} \right) = \begin{array}{l} \text{Mother,} \\ \text{Employed,} \\ \text{Observed } \vec{x}_i \end{array}$$

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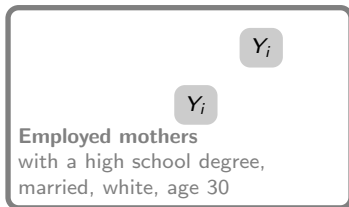


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↓
Any prediction algorithm
that minimizes squared errors

$$\longrightarrow E \left(Y_i \mid \begin{array}{l} \text{Motherhood} \\ \text{Employment} \\ \text{Covariates } \vec{X} \end{array} = \begin{array}{l} \text{Mother,} \\ \text{Employed,} \\ \text{Observed } \vec{x}_i \end{array} \right)$$

Realized outcomes





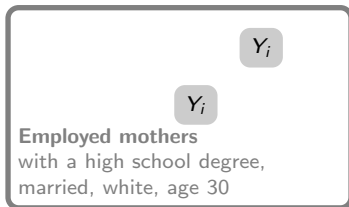
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Any prediction algorithm
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Generalized
Additive
Model

Realized outcomes



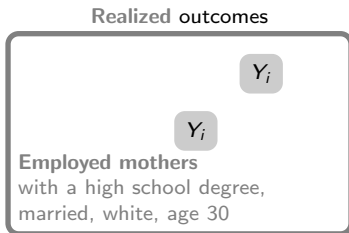


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Any prediction algorithm
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Generalized Additive Model Random Forest



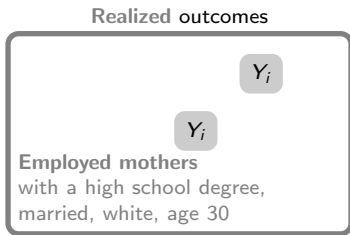


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Any prediction algorithm
that minimizes squared errors

Ordinary Least Squares Generalized Additive Model Random Forest





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



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

1) Learn an algorithm to predict the outcome



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

- 1) Learn an algorithm to predict the outcome
- 2) Predict for every unit at each treatment value

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



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

- 1) Learn an algorithm to predict the outcome
- 2) Predict for every unit at each treatment value

$$\hat{Y}_i \left(\begin{matrix} \text{Mother,} \\ \text{Employed} \end{matrix} \right) = \hat{E} \left(Y_i \left| \begin{array}{l} \text{Motherhood} = \text{Mother,} \\ \text{Employment} = \text{Employed,} \\ \text{Covariates } \vec{X} = \text{Observed } \vec{x}_i \end{array} \right. \right)$$



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

- 1) Learn an algorithm to predict the outcome
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$$\hat{Y}_i \begin{pmatrix} \text{Non-mother,} \\ \text{Employed} \end{pmatrix} = \hat{E} \left(Y_i \left| \begin{array}{l} \text{Motherhood} = \text{Non-mother,} \\ \text{Employment} = \text{Employed,} \\ \text{Covariates } \vec{X} = \text{Observed } \vec{x}_i \end{array} \right. \right)$$



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

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$$\hat{Y}_i \left(\begin{matrix} \text{Mother,} \\ \text{Employed} \end{matrix} \right) - \hat{Y}_i \left(\begin{matrix} \text{Non-mother,} \\ \text{Employed} \end{matrix} \right)$$



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

- 1) Learn an algorithm to predict the outcome
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- 3) Average over the target population

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



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

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This is called an **imputation estimator**

Hahn, 1998

Abadie & Imbens 2006

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



Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status



Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

Least flexible

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

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Choose an algorithm by **predictive performance**

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Least flexible OLS with a quadratic for age
+ Interaction between age and motherhood

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Choose an algorithm by **predictive performance**

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Predictors Motherhood, age, race, education, marital status

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Least flexible OLS with a quadratic for age
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Most flexible



Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

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Least flexible OLS with a quadratic for age
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+ Include each age as a separate indicator variable

Most flexible



Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

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Least flexible	OLS with a quadratic for age
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Most flexible	+ Include all interactions among all predictors



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Choices about **functional form**



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
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Choices about **functional form** are best decided by the data



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

Best predictions

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

Most flexible + Include all interactions among all predictors

Choices about **functional form** are best decided by the data



Our framework partitions research choices

Some choices must be **theory-driven**

- What question is important?
- What variables should I adjust?

theoretical estimand
empirical estimand

Some choices can be **data-driven**

- Do I include a squared term?
- Do I need an interaction?

estimation strategy



Replication 2

Coefficient-based reasoning hampers understanding

	β	(SE)
Birth Cohort 1966+ (vs. 1938–1965)	.318	(.285)
Female	–.136	(.133)
Later Cohorts \times Female	–.107	(.272)
Mother Some College	.737**	(.134)
Later Cohorts \times Mother Some College	.079	(.218)
No Father Present	–.031	(.129)
Father Some College	1.285**	(.113)
Later Cohorts \times No Father	–.107	(.226)
Later Cohorts \times Father Some College	–.390	(.211)
Mother Some College \times Female	.120	(.147)
No Father Present \times Female		
Father Some College \times Female		
Mother Some College \times No Father	.108	(.208)
Mother Some College \times Father Some College	.150	(.138)
No Father or Father \leq HS \times Male	.303*	(.143)
No Father or Father \leq HS \times Male \times Later Cohorts	–.801**	(.293)
Mother Some College \times Female \times Later Cohorts	.221	(.295)
No Father \times Female \times Later Cohorts		
Father Some College \times Male \times 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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Descriptive Proportion completing college
estimand: within subgroups of the predictors

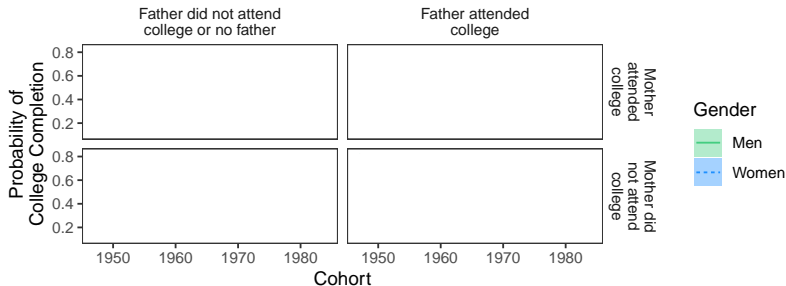


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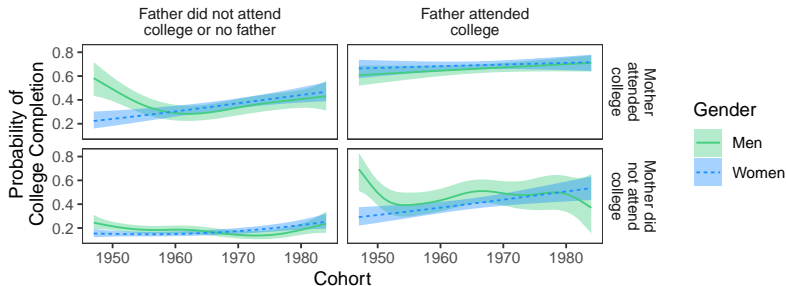


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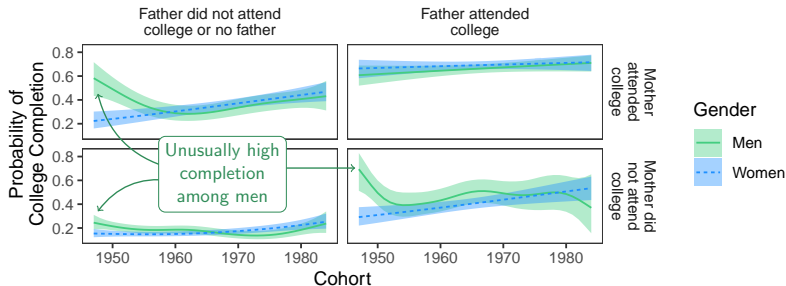


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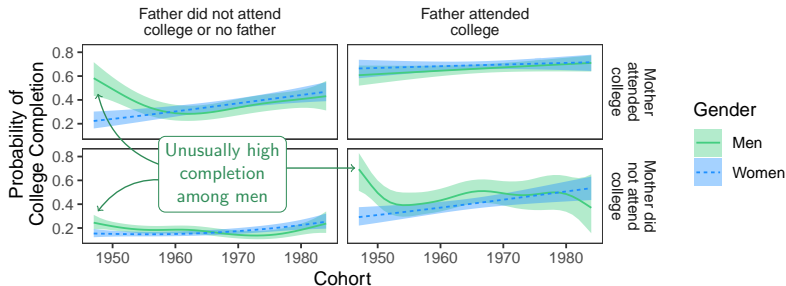


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Alternate theory: The Vietnam War



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:

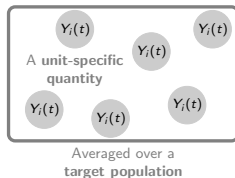
- 1) Distinguish causal treatments from population labels
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Document widespread vagueness in *ASR*

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

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand





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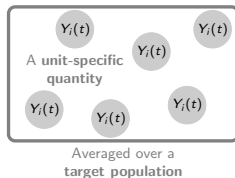
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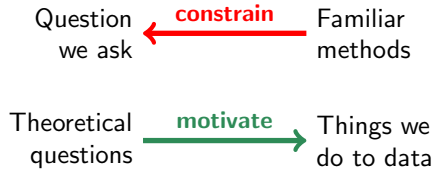
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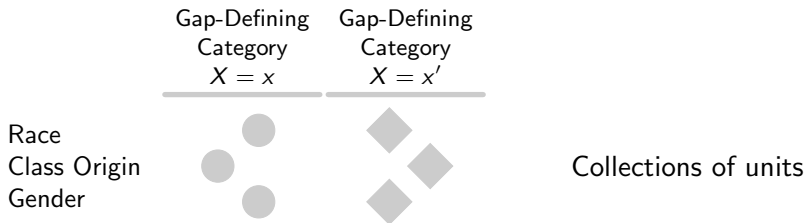
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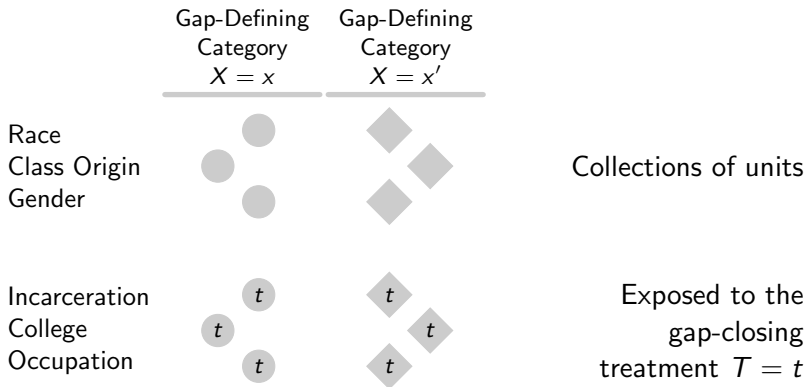
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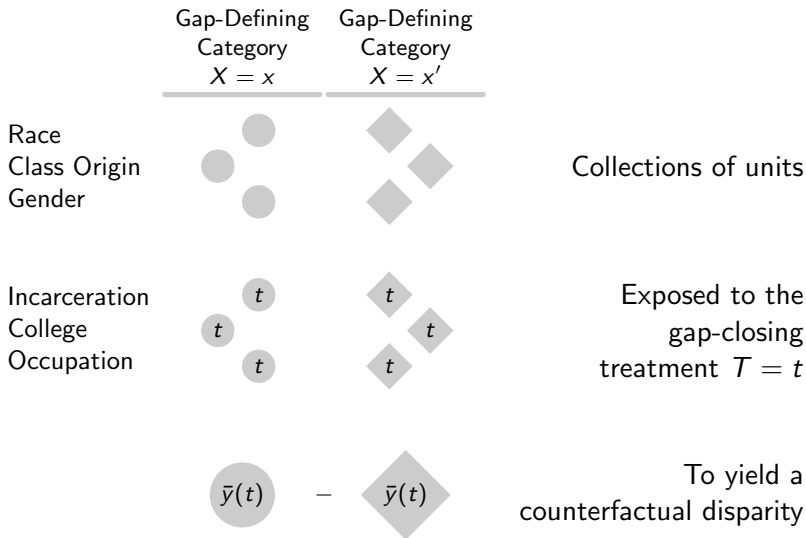
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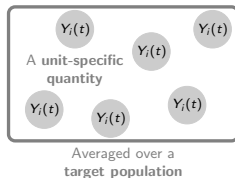
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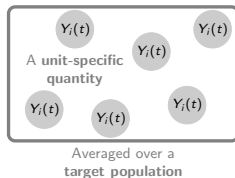
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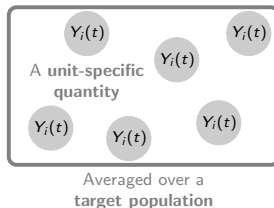
→ **Discuss** Every quantitative study should define the estimand





What is your estimand?

← Every quantitative study should answer this question

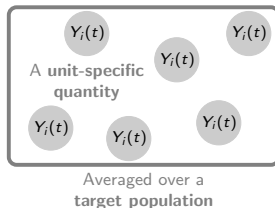




What is your estimand?

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



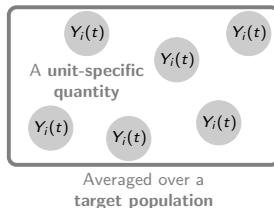


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When you **write** a quantitative paper, the estimand allows you to

— Motivate the question outside the model



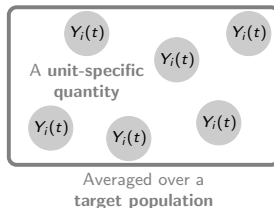


What is your estimand?

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

- Motivate the question outside the model
- Address selection transparently



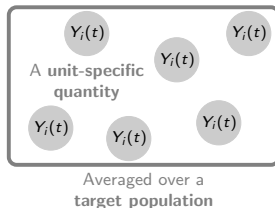


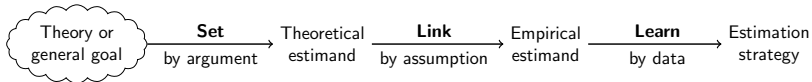
What is your estimand?

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

- Motivate the question outside the model
- Address selection transparently
- Unlock computational tools



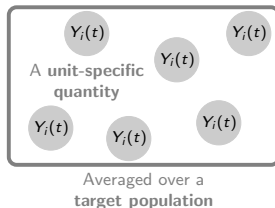


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When you **write** a quantitative paper, the estimand allows you to

- Motivate the question outside the model
- Address selection transparently
- Unlock computational tools
- Present interpretable summaries



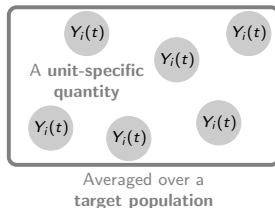


What is your estimand?

← 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

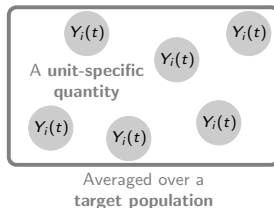




What is your estimand?

← Every quantitative study should answer this question

In the future, estimands will only become more important





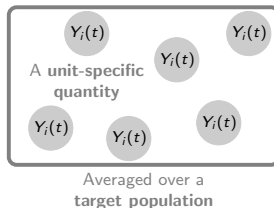
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New data have missing values

- Non-probability samples
- Administrative records





What is your estimand?

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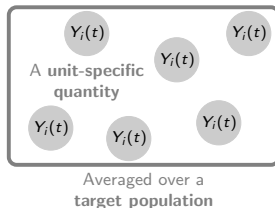
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New methods flourish with a clear goal

- Machine learning





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In the future, estimands will only become more important

New data have missing values

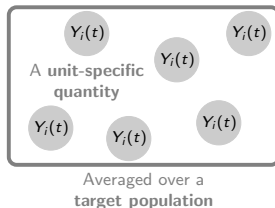
- Non-probability samples
- Administrative records

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





What is your estimand?

← Every quantitative study should answer this question

Defining the Target Quantity
Connects Statistical Evidence
to Theory

Ian Lundberg

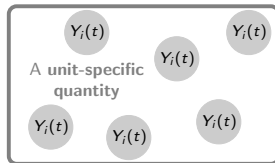
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Averaged over a
target population

Draft on [SocArxiv](#)
Code on [Dataverse](#)

Forthcoming, *American Sociological Review*