What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

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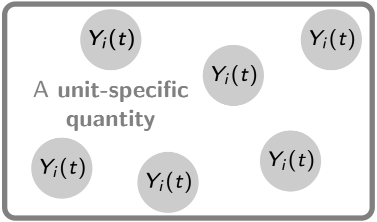

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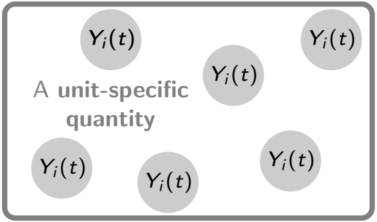

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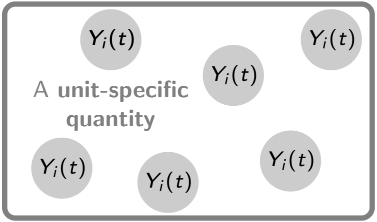

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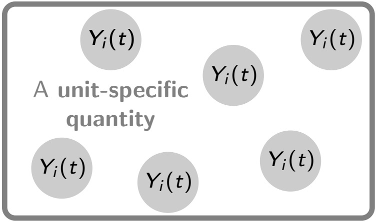

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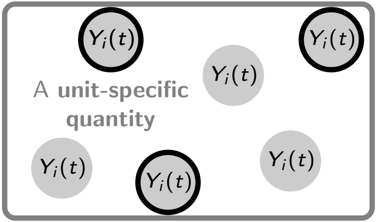

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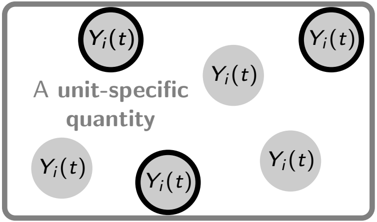

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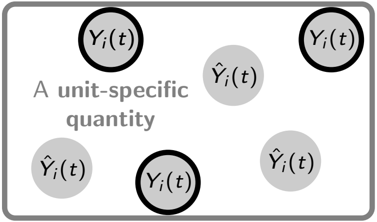

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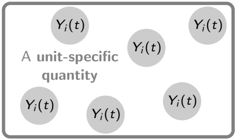
Document widespread vagueness in *ASR*

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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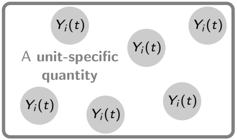

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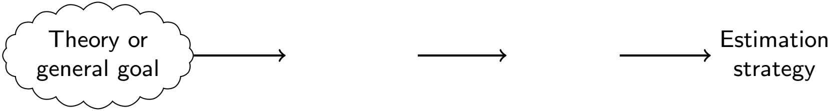
Research framework: Estimands connect theory to evidence



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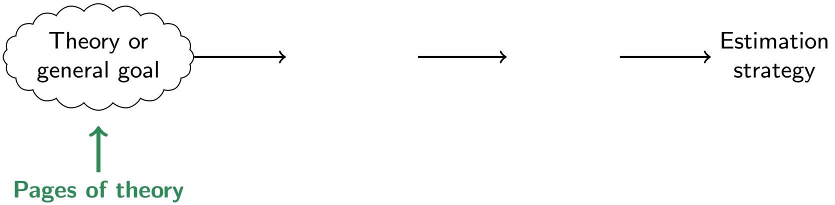

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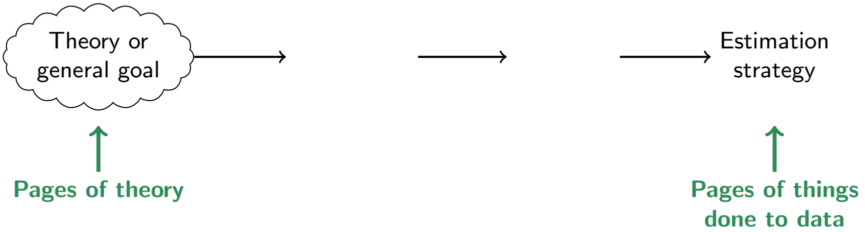

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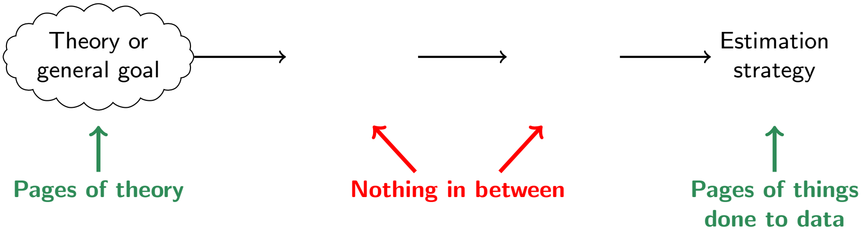

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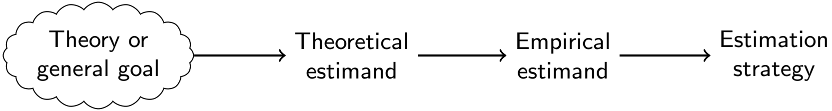

Research framework: Estimands connect theory to evidence

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

Set a specific target

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Definition

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

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

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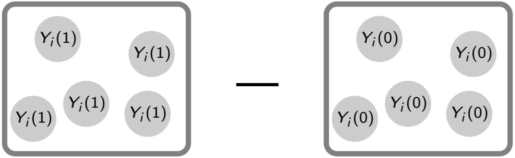
A **unit-specific quantity** aggregated over a **target population**	

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Link to observable data

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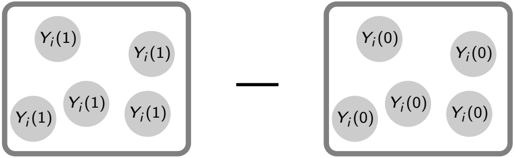
A quantity involving **observable data**	

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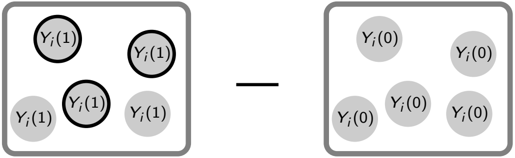
A quantity involving **observable data**	

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

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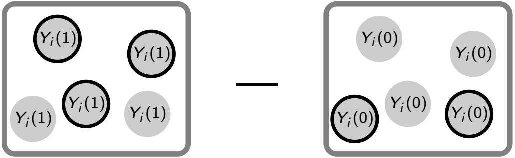
A quantity involving **observable data**	

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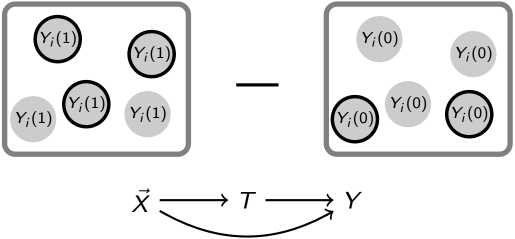
A quantity involving **observable data**	

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

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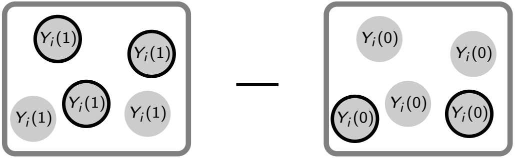
An algorithm applied to data	

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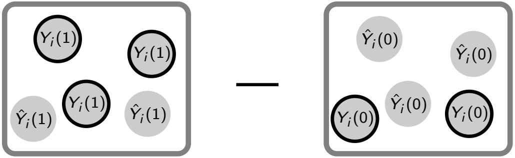
An algorithm applied to data	

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

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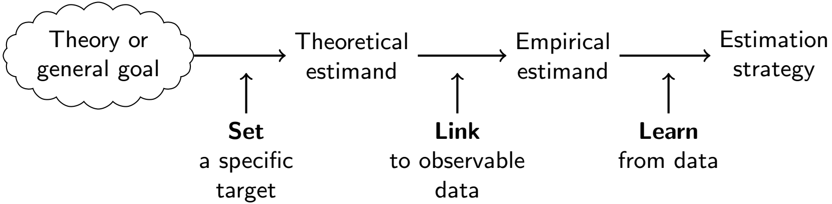

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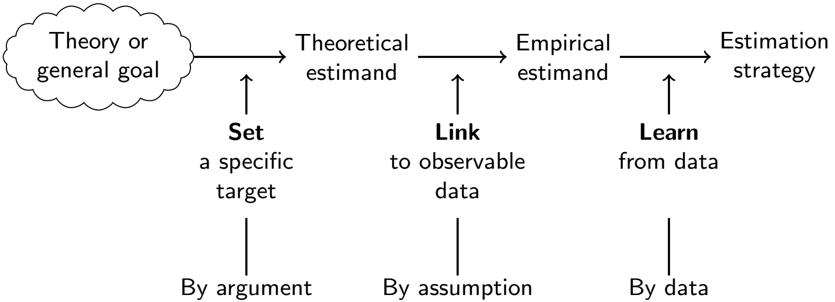

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Illustrate through four examples. We have to:

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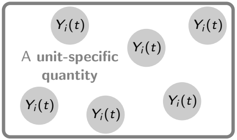

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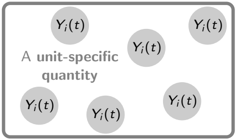

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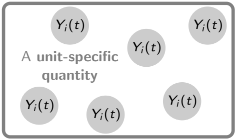

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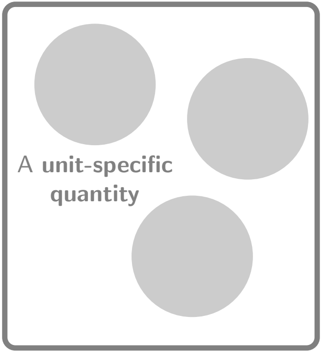

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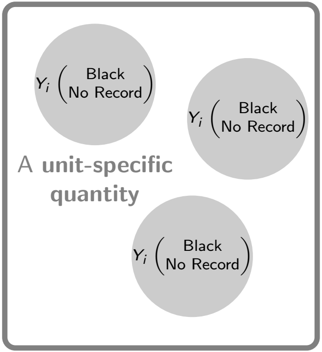

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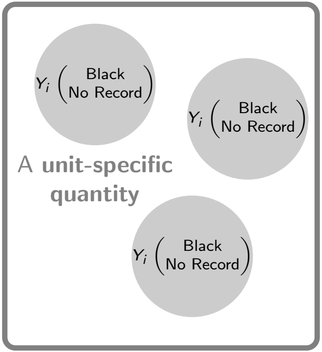

Averaged over all **applications**

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

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


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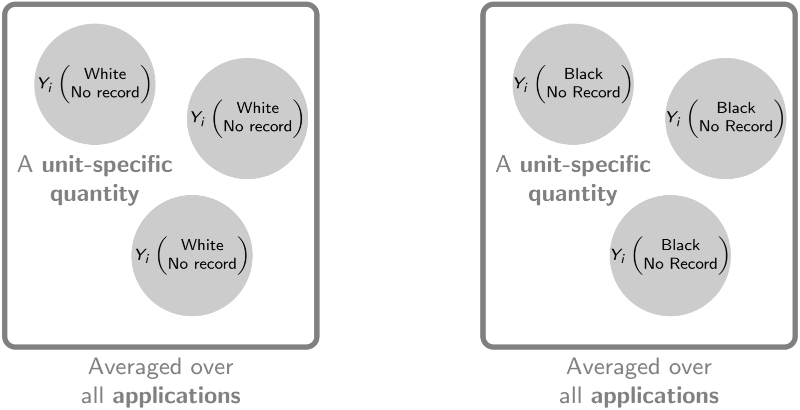
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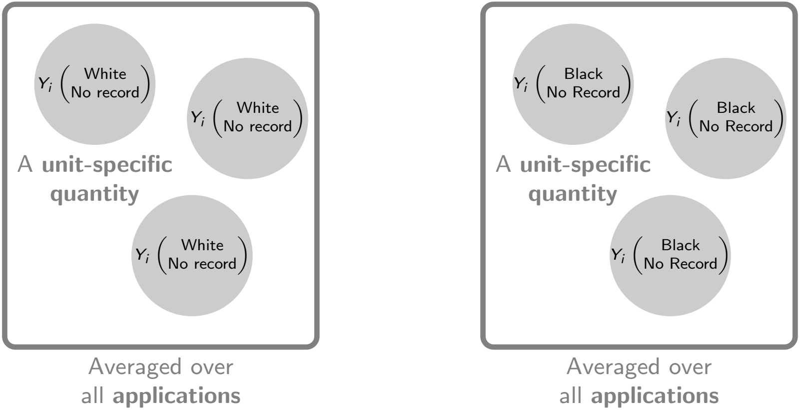
Discrimination: One population of applications



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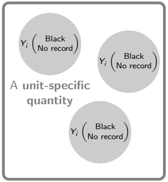
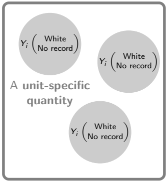
Estimand 1: Racial **discrimination**



Averaged over all **applications**



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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

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

Y_i(No record)

A **unit-specific quantity**

Y_i(No record)

Y_i(No record)

Averaged over **black applicants**

Y_i(No record)

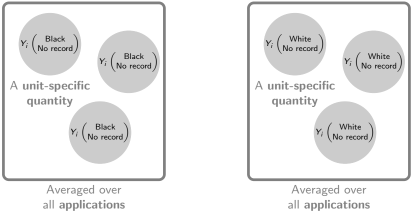
A **unit-specific quantity**

Y_i(No record)

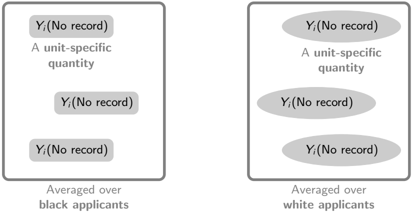
Y_i(No record)

Averaged over **white applicants**

Estimand 1: Racial **discrimination**

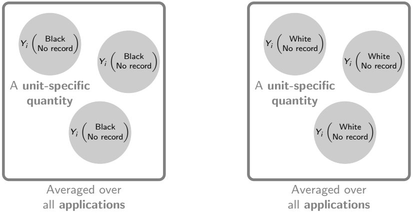


Estimand 2: Racial **disparity** under ban-the-box



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

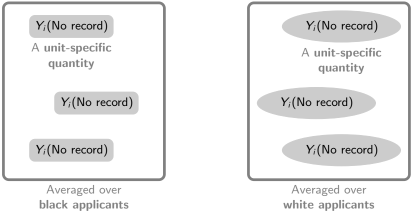
Estimand 1: Racial **discrimination**



Two treatment conditions

One population

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



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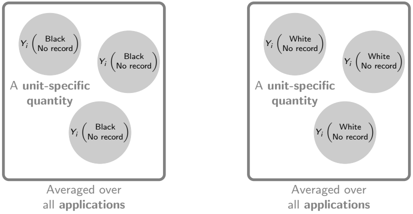

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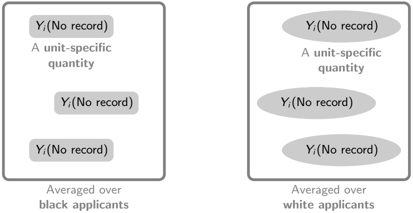
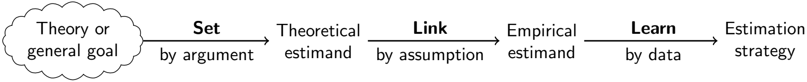


One treatment condition

Two populations



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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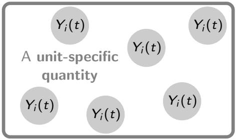
4) Beware of causal selection in descriptive claims

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**

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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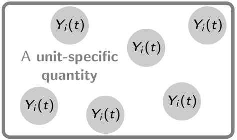

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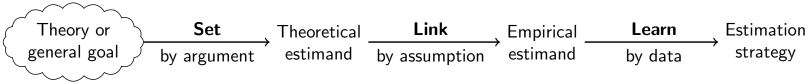

Angrist and Evans 1998

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

Effect of motherhood
on employment

Angrist and Evans 1998

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Effect of motherhood
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First two births
are the same sex

Angrist and Evans 1998

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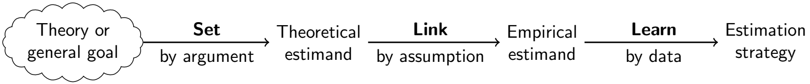
First two births are the same sex $\longrightarrow$ Third birth

Angrist and Evans 1998



Effect of motherhood
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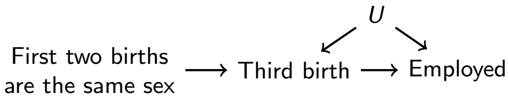

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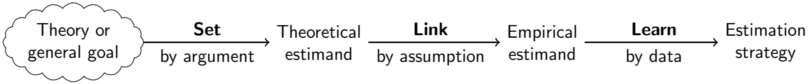

Vague estimand

Effect of motherhood
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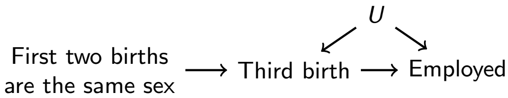

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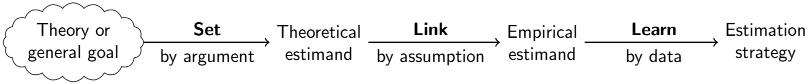
Vague estimand

Effect of motherhood on employment

Precise estimand

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

Angrist and Evans 1998



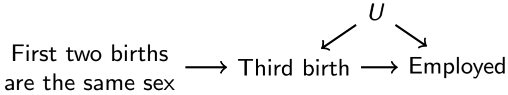
unit-specific quantity

Vague estimand

Effect of motherhood on employment

Precise estimand

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



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Vague estimand

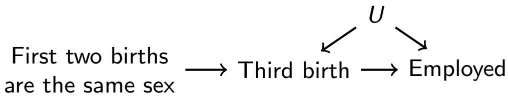
Effect of motherhood on employment

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]



Angrist and Evans 1998

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

$$\approx 4\% \text{ of all mothers}$$

Angrist and Evans 1998

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

You have to argue either:

1)

2)

Angrist and Evans 1998

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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

You have to argue either:

1) That estimand matters for theory, or

2)

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:

1) That estimand matters for theory, or

2) It speaks to some broader estimand

Angrist and Evans 1998

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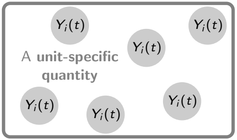

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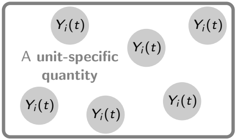

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Example: Age-standardized mortality

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

Example: Age-standardized mortality

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

Example: Age-standardized mortality

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

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

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.

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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Descriptive Estimand **Causal 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

Example: Age-standardized mortality

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

Age-specific mortality
is descriptive

Causal Estimand

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Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

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Causal Estimand

Problem: Why adjust for age?

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Causal Estimand

Problem: Why adjust for age?

Why not obesity,

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

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Identified ✓

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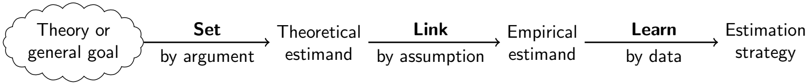
Meaningful ?



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Causal Estimand

The "effect" of social context

Identified ✓

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Causal Estimand

The “effect” of social context

A “counterfactual” population

Identified ✓

Meaningful ?

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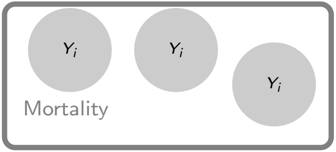

Averaged over the U.S. population

Identified ✓

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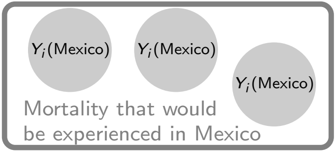

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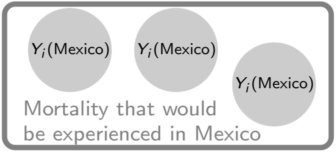

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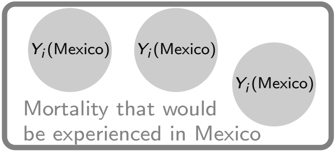

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1. Estimate mortality in the U.S. and Mexico at each age.
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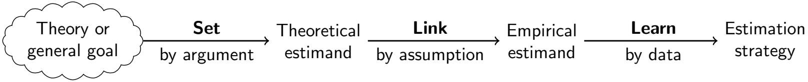
3. Report the disparity between the two countries.

This same issue applies to
all sociological studies
reporting **adjusted disparities**.



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Illustrate through four examples. We have to:

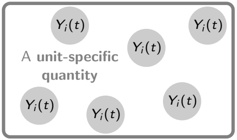
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

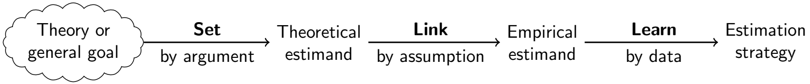
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



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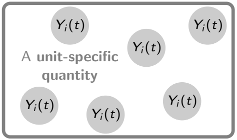

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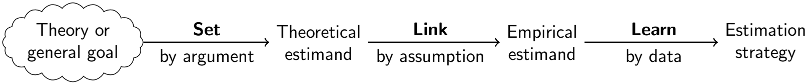

An Empirical Analysis of Racial Differences in Police Use of Force

Roland G. Fryer Jr.

Harvard University and National Bureau of Economic Research

This paper explores racial differences in police use of force. On nonlethal 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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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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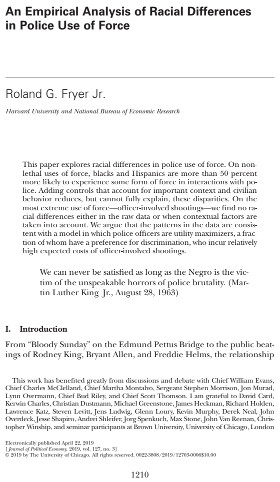

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Evidence:

Claim:

Why wrong:

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

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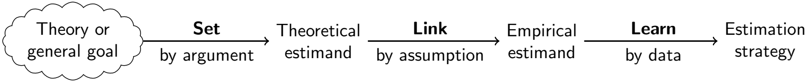

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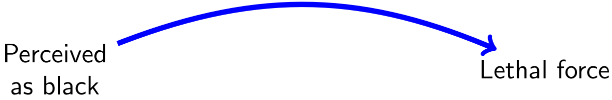

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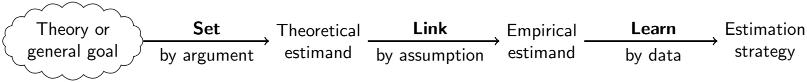

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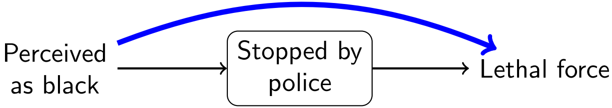

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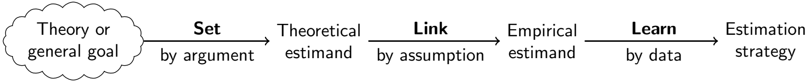

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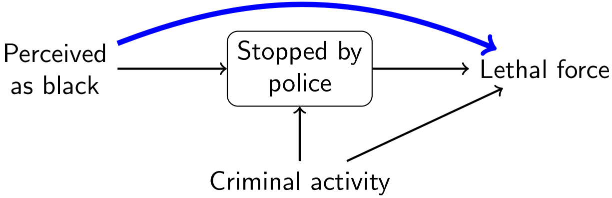

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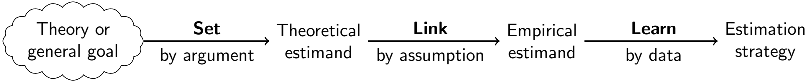

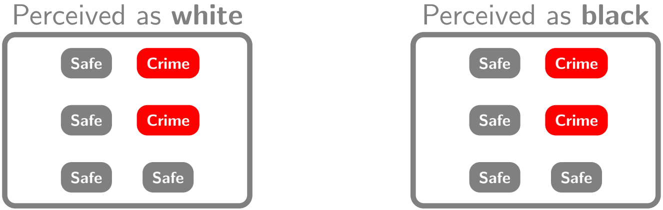

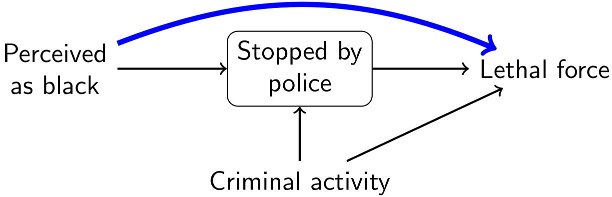

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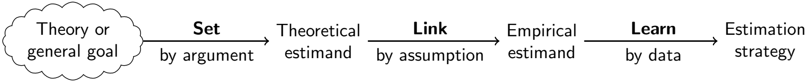

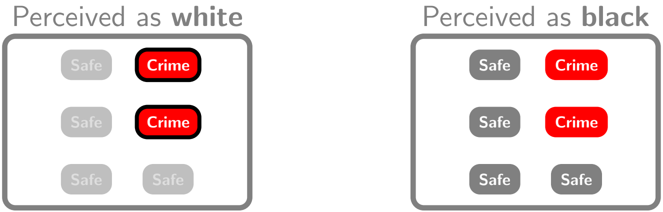

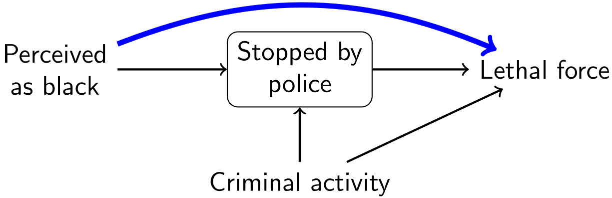

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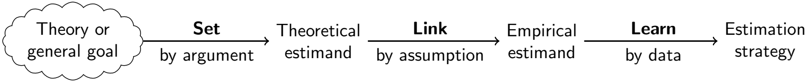

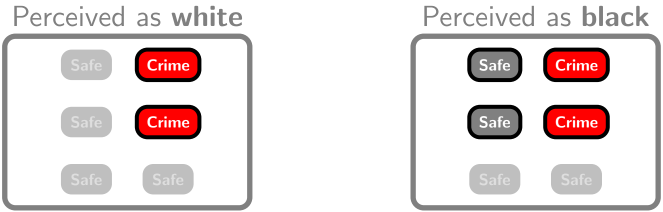

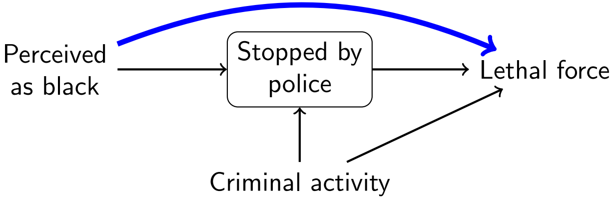

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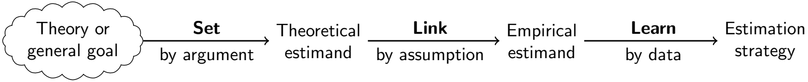

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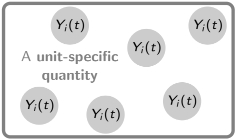

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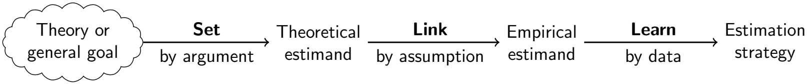

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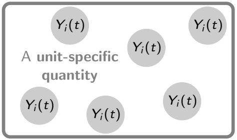

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Review

All 32 articles in ASR 2018 using quantitative data

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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* → Causal target: Observational data

7 articles | 22% of *ASR* → Causal target: Experiments

7 articles | 22% of *ASR* → Descriptive target

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Causal target: Observational data	Causal target: Experiments	Descriptive target
0 out of 18 articles was clear	**4 out of 7** articles were clear	**1 out of 7** articles was clear

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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

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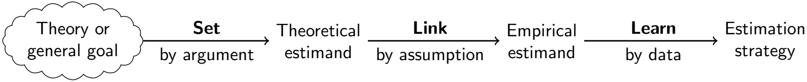
Probability samples	Administrative records	Other samples
6 out of 16 articles were clear	**1 out of 6** articles was clear	**2 out of 10** articles were clear



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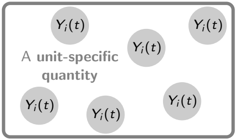

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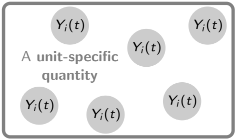

Averaged over a **target population**

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.

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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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"

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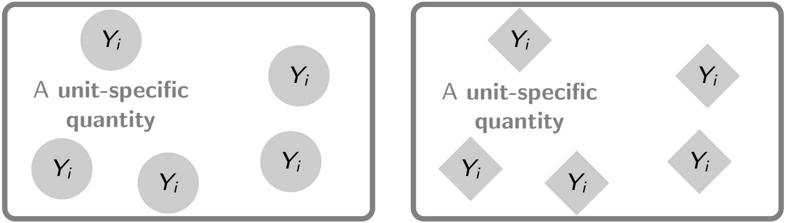

Averaged over a **target population** of **mothers**

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

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

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"causal estimation techniques"

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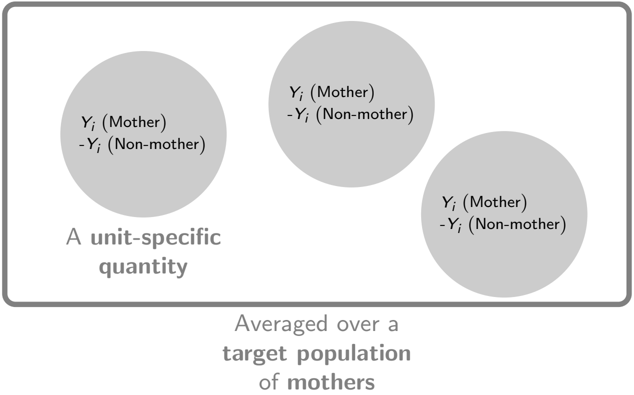

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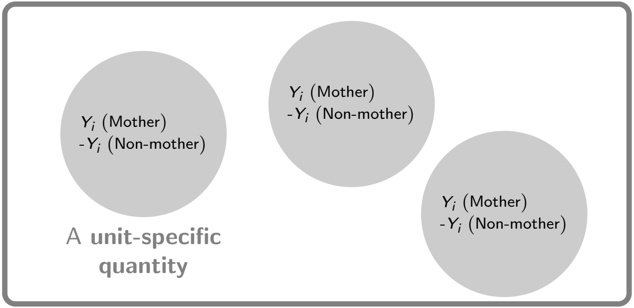
Is the theoretical estimand descriptive? Is it causal?

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



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

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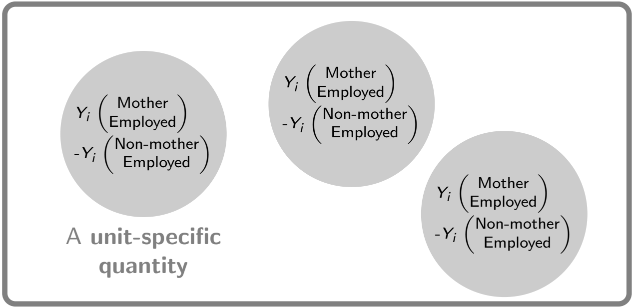

Averaged over a **target population** of **mothers**

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

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

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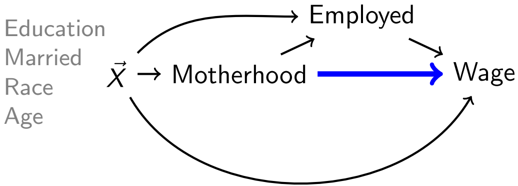

Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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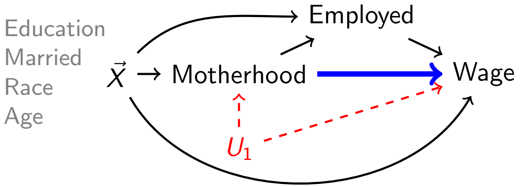

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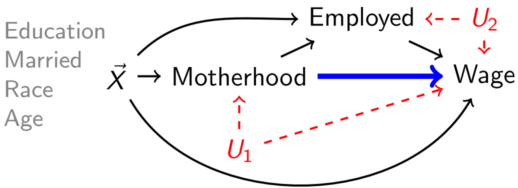

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Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\\text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\\text{Employed}\end{pmatrix}$

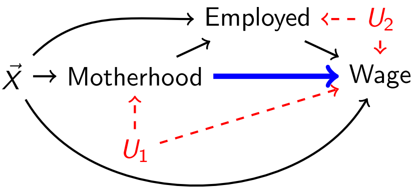
Potential outcomes

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

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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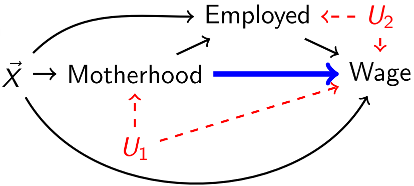

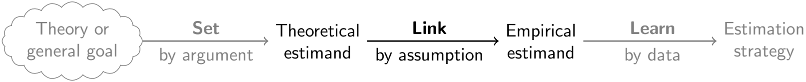

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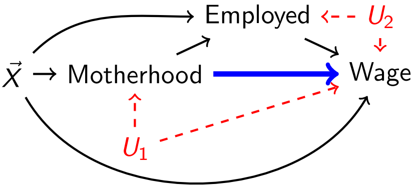

Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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

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

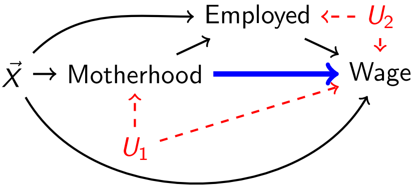
Realized outcomes

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 → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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

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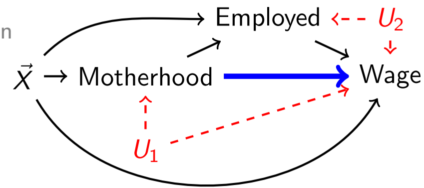

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Realized outcomes

Y_i

Y_i

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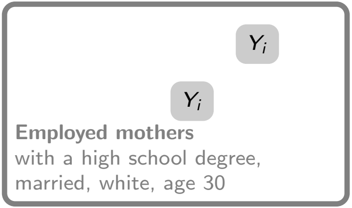
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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



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

Any prediction algorithm that minimizes squared errors

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

Realized outcomes

Y_i

Y_i

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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

Generalized Additive Model

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**!

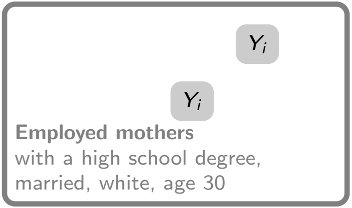
$$\text{E}\left(Y_i \,\middle|\, \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,} \\ \text{Employment} & = & \text{Employed,} \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

Any prediction algorithm that minimizes squared errors

Generalized Additive Model

Random Forest

Realized outcomes



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

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

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

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

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

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

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

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

3) Average over the target population

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

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

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

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

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

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

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

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**

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
+ Include each age as a separate indicator variable

Most flexible

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

Candidate algorithms

Least flexible	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
Most flexible	+ Include all interactions among all predictors

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

Candidate algorithms

Least flexible	OLS with a quadratic for age
	+ Interaction between age and motherhood
	+ Allow a smooth curve for age rather than quadratic
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Most flexible	+ Include all interactions among all predictors

Choices about **functional form**

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

Candidate algorithms

Least flexible	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
Most flexible	+ Include all interactions among all predictors

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

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
Best predictions	+ 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

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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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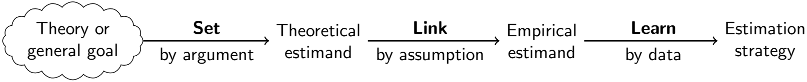
Descriptive estimand: Proportion completing college within subgroups of the predictors



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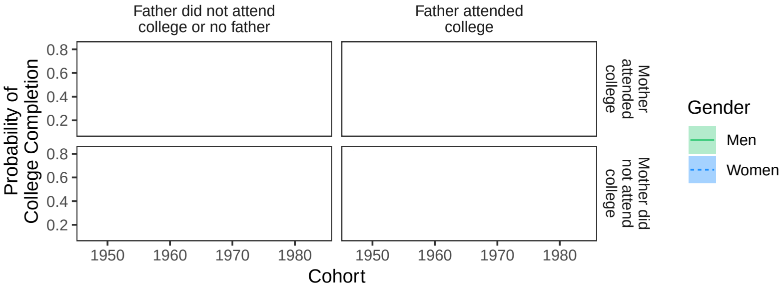

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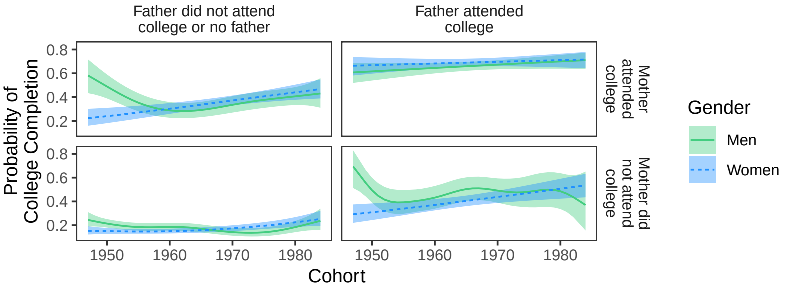

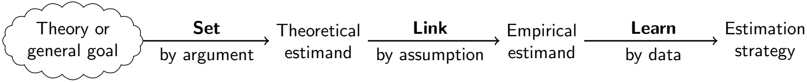

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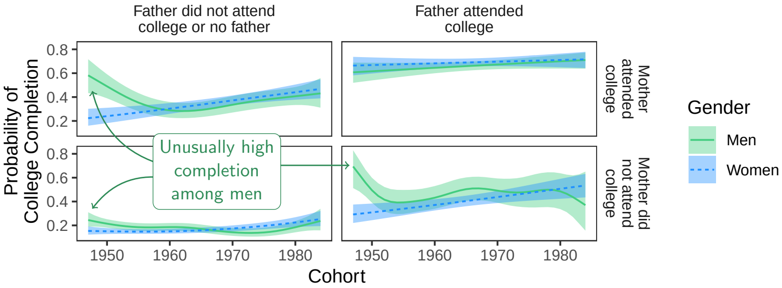

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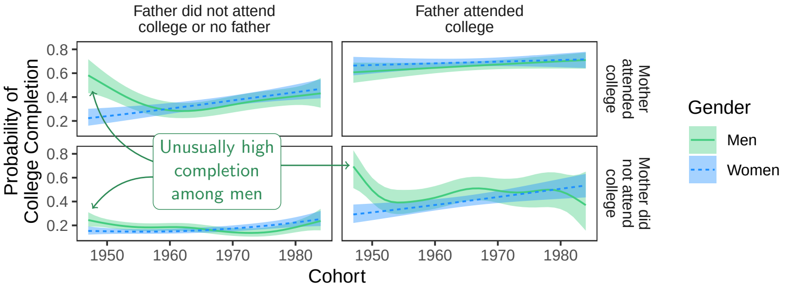

Alternate theory: The Vietnam War

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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:

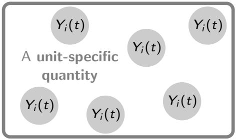
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

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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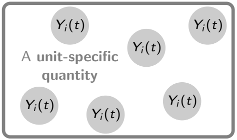

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The Gap-Closing Estimand:
A Causal Approach to Study Interventions
That Close Disparities Across Social Categories

Lundberg, Ian
Working paper
On SocArxiv

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

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

Theoretical questions $\xrightarrow{\textbf{motivate}}$ 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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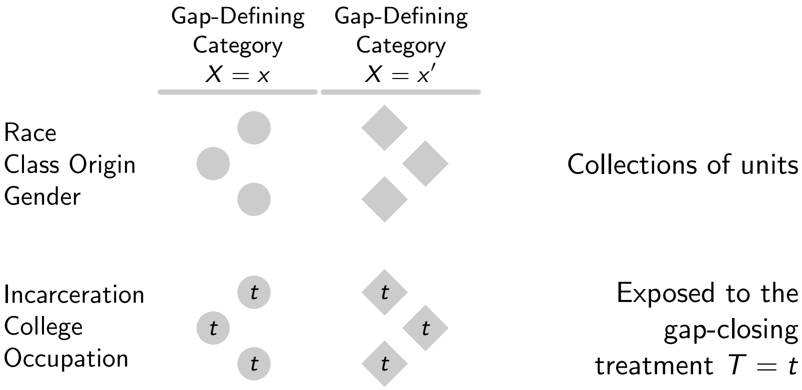

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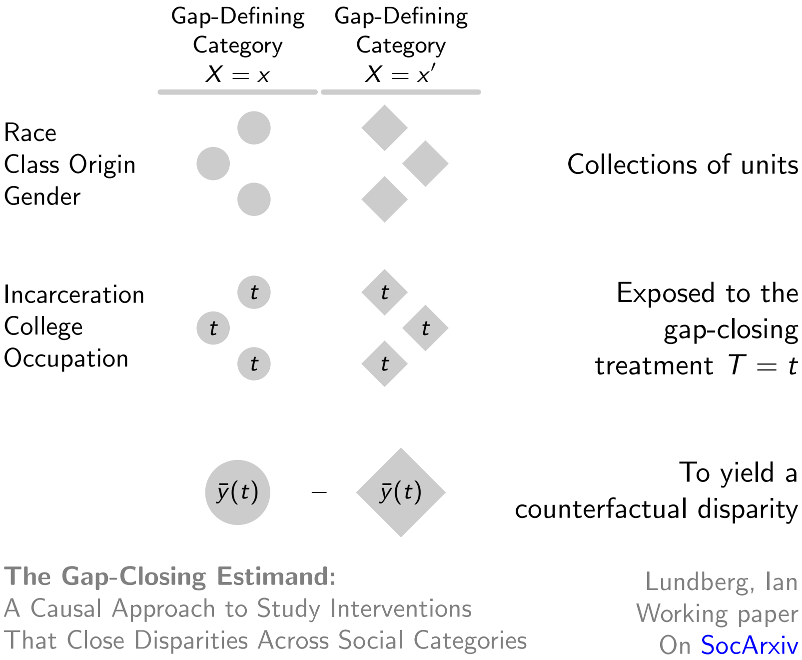
Gap-Defining Category $X = x$
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Class Origin
Gender
Collections of units
Incarceration
College
Occupation
t
t
t
t
t
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Exposed to the gap-closing treatment $T = t$
$\bar{y}(t)$
$-$
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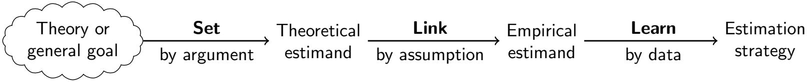

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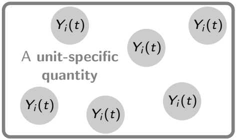

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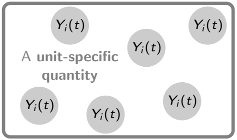

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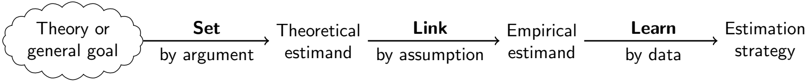

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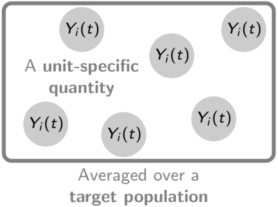

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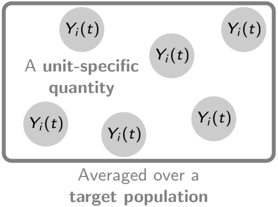
When you **write** a quantitative paper, the estimand allows you to



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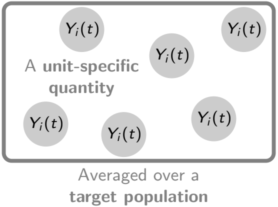
When you **write** a quantitative paper, the estimand allows you to

— Motivate the question outside the model



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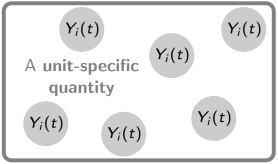

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When you **write** a quantitative paper, the estimand allows you to

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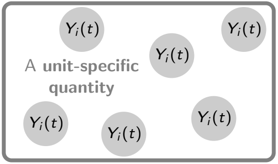
— Unlock computational tools



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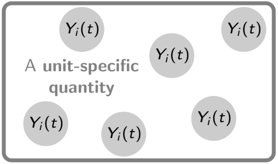
— Present interpretable summaries



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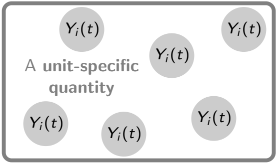
When you **read** a quantitative paper, the estimand allows you to

— Understand the author's aim

— Pinpoint your concerns



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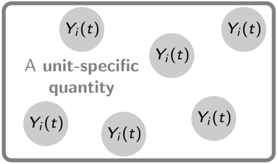

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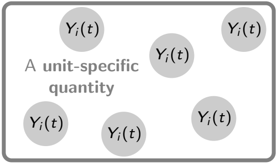
New data have missing values

— Non-probability samples

— Administrative records



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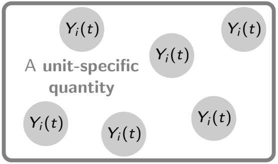
— Machine learning



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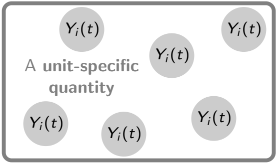

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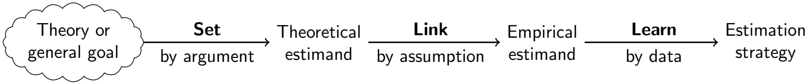
New questions can be found beyond coefficients

— Describe counterfactual disparities

— Predict the effects of targeted interventions



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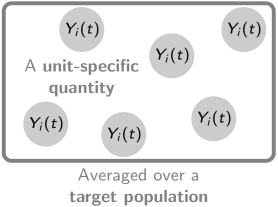

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Draft on SocArxiv
Code on Dataverse
Forthcoming, *American Sociological Review*