What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Ian Lundberg

Princeton
Sociology
ianlundberg.org

Rebecca Johnson

Dartmouth Quantitative
Social Science
rebeccajohnson.io

Brandon M. Stewart

Princeton
Sociology
brandonstewart.org

18 September 2020.
Forthcoming in *American Sociological Review*. Draft on SocArxiv. Replication code on Dataverse. Research reported in this publication was supported by The Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health under Award Number P2CHD047879.

There is a question every quantitative study must answer:

There is a question every quantitative study must answer:

What is your estimand?

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

There is a question every quantitative study must answer:

What is your estimand?

A common answer:

The **purpose** of the statistical analysis

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

The model is an approximation

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

So β_1 is an approximation to...

The model is an approximation

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

The model is an approximation

So β_1 is an approximation to...

Something. I just haven't said what.

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

The model is an approximation

So β_1 is an approximation to...

Something. I just haven't said what.

Is it a good approximation?

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

A common answer:

— We took [data source]

— We estimated β_1

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

β_1 is an estimand that assumes a model

What if the model is wrong?

The model is an approximation

So β_1 is an approximation to...

Something. I just haven't said what.

Is it a good approximation?

Epistemological crisis

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the
statistical analysis

stated **outside**
of the model

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model

A **unit-specific quantity**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model

Y_i

A **unit-specific quantity**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model

$Y_i(t)$

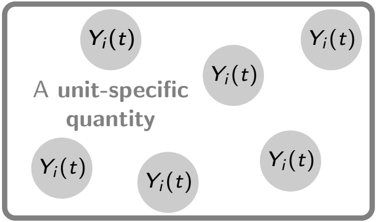
A **unit-specific quantity**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



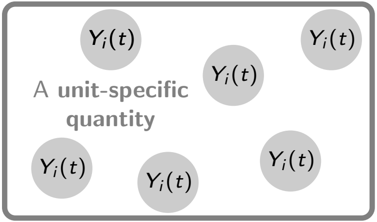
Aggregated over a **target population**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

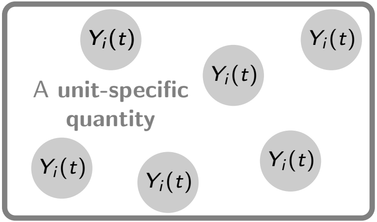
and unlocks computational **tools**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

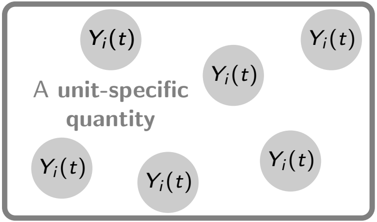
and unlocks computational **tools**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

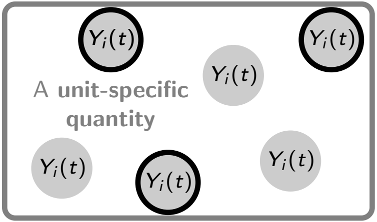
and unlocks computational **tools**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

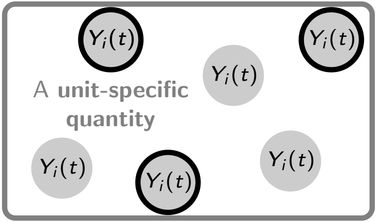
and unlocks computational **tools**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

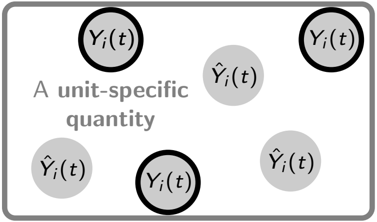
and unlocks computational **tools**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



Aggregated over a **target population**

Our framework expands **theory**,

links to transparent **evidence**,

and unlocks computational **tools**

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

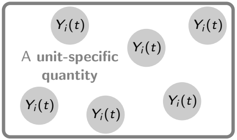
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

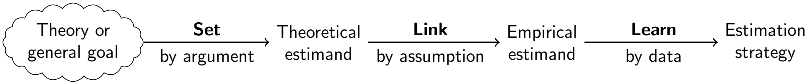
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

→ **Introduce** a framework for quantitative social science

Illustrate through four examples. We have to:

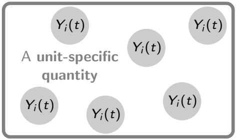
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

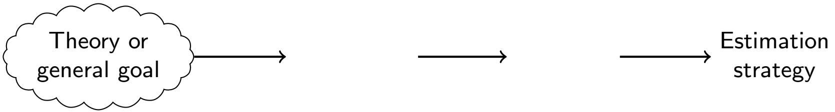
Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

Research framework: Estimands connect theory to evidence



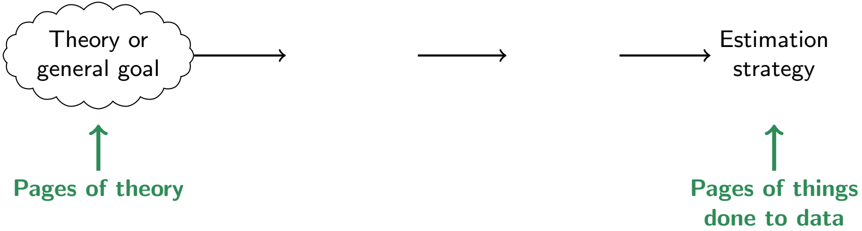
Research framework: Estimands connect theory to evidence

Theory or general goal ⟶ ⟶ ⟶ Estimation strategy

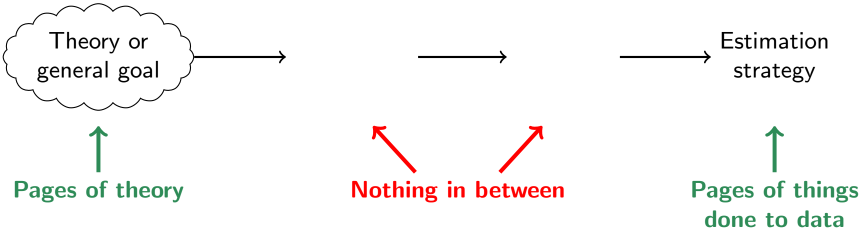
↑

Pages of theory

Research framework: Estimands connect theory to evidence



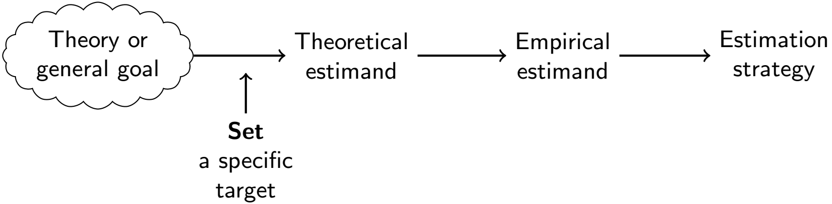
Research framework: Estimands connect theory to evidence



Research framework: Estimands connect theory to evidence

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

Research framework: Estimands connect theory to evidence



Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Definition

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

Research framework: Estimands connect theory to evidence

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

$\uparrow$

Set a specific target

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

Research framework: Estimands connect theory to evidence

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

Set a specific target

Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$\frac{1}{\text{Size of U.S. adult population}} \sum_{\substack{i \text{ in U.S.} \\ \text{adult population}}} \left(\underbrace{\text{Employed}_i(\text{Job training})}_{\substack{\text{Employment if received} \\ \text{job training}}} - \underbrace{\text{Employed}_i(\text{No job training})}_{\substack{\text{Employment if did not receive} \\ \text{job training}}} \right)$

Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \left(\underbrace{\text{Employed}_i(\text{Job training})}_{\text{Employment if received job training}} - \underbrace{\text{Employed}_i(\text{No job training})}_{\text{Employment if did not receive job training}} \right)$

Lieberson 1987, Abbott 1988, Freedman 1991, Xie 2013, Hernán 2018

Research framework: Estimands connect theory to evidence

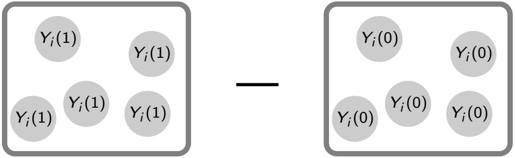
Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Definition

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

Example



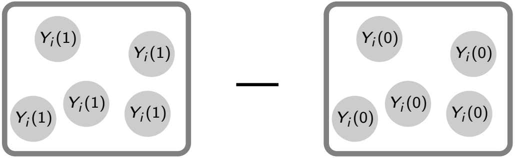
Lieberson 1987, Abbott 1988, Freedman 1991, Xie 2013, Hernán 2018

Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Link to observable data

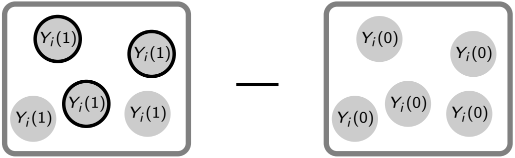
Definition	Example
A quantity involving **observable data**	

Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Link to observable data

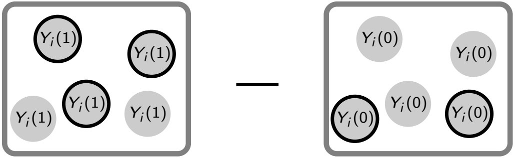
Definition	Example
A quantity involving **observable data**	

Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Link to observable data

Definition	Example
A quantity involving **observable data**	

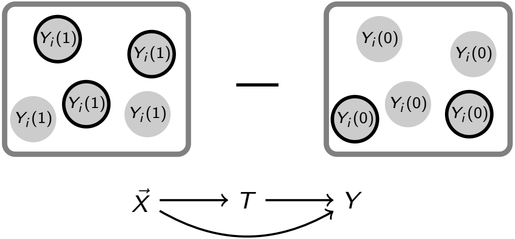
Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

Link to observable data

Definition	Example
A quantity involving **observable data**	



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

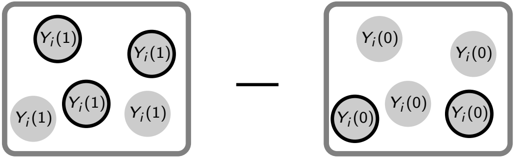
Research framework: Estimands connect theory to evidence

Theory or general goal → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

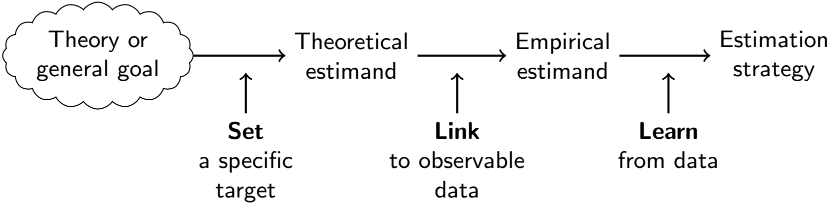
Link to observable data

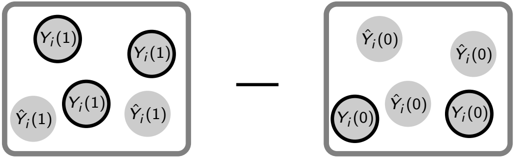
Learn from data

Definition	Example
An algorithm applied to data	

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

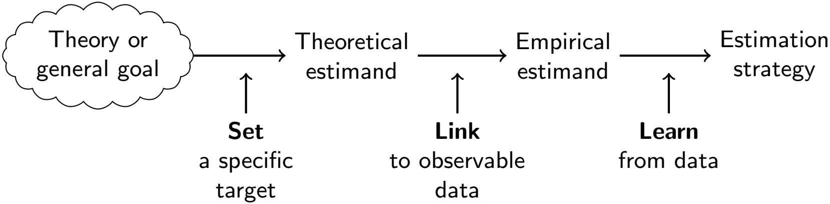
Research framework: Estimands connect theory to evidence



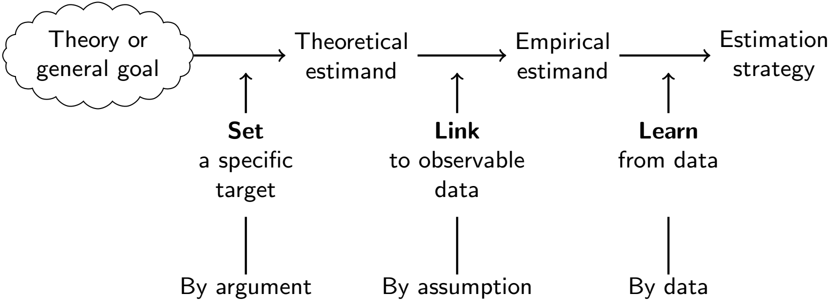
Definition	Example
An algorithm applied to data	

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

Research framework: Estimands connect theory to evidence



Research framework: Estimands connect theory to evidence



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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

→ **Introduce** a framework for quantitative social science

Illustrate through four examples. We have to:

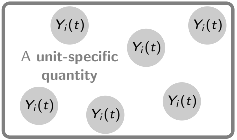
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

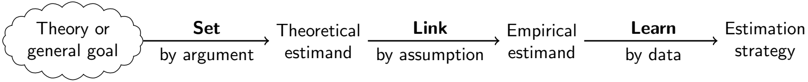
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

→ **Illustrate** through four examples. We have to:

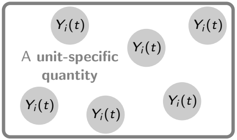
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

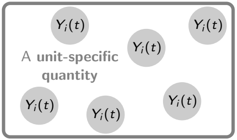
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

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

Pager (2003) explores

"the ways in which
the effects of race and
criminal record interact to
produce new forms
of labor market inequalities."

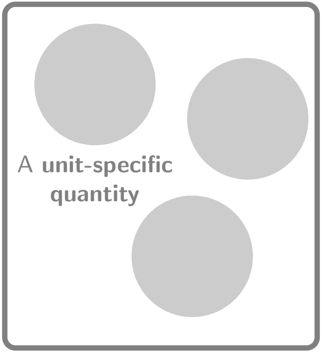
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Pager (2003) explores

"the ways in which
the effects of race and
criminal record interact to
produce new forms
of labor market inequalities."

Pager (2003) explores

“the ways in which
the effects of race and
criminal record interact to
produce new forms
of labor market inequalities.”

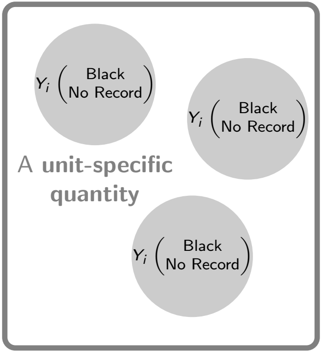


Averaged over a
all applications

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

Pager (2003) explores

"the ways in which
the effects of race and
criminal record interact to
produce new forms
of labor market inequalities."

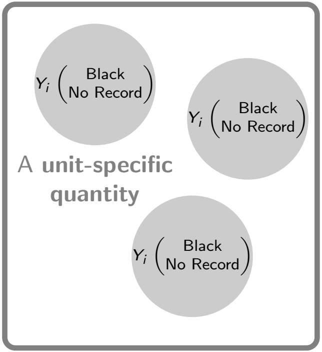


Averaged over
all **applications**

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

Pager (2003) explores

"the ways in which the effects of race and criminal record interact to produce new forms of labor market inequalities."

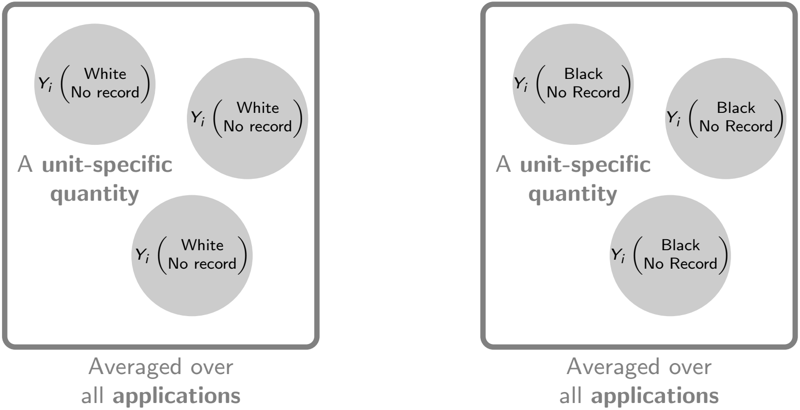


Averaged over all **applications**

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

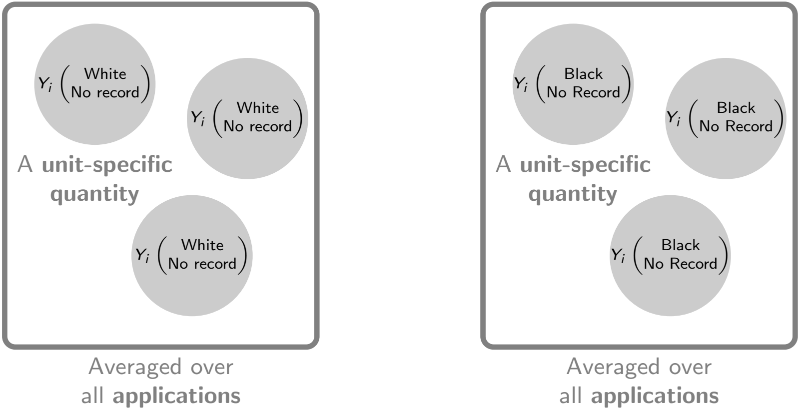
Greiner & Rubin 2011, Sen & Wasow 2016, Kohler-Hausmann 2018


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

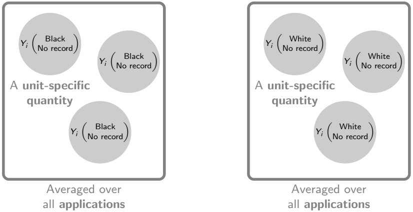

$Y_i\begin{pmatrix}\text{White}\\\text{No record}\end{pmatrix}$
$Y_i\begin{pmatrix}\text{White}\\\text{No record}\end{pmatrix}$
A **unit-specific quantity**
$Y_i\begin{pmatrix}\text{White}\\\text{No record}\end{pmatrix}$
Averaged over all **applications**
$Y_i\begin{pmatrix}\text{Black}\\\text{No Record}\end{pmatrix}$
$Y_i\begin{pmatrix}\text{Black}\\\text{No Record}\end{pmatrix}$
A **unit-specific quantity**
$Y_i\begin{pmatrix}\text{Black}\\\text{No Record}\end{pmatrix}$
Averaged over all **applications**

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

Discrimination: One population of applications



Estimand 1: Racial **discrimination**



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

Estimand 2: Racial **disparity** 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)

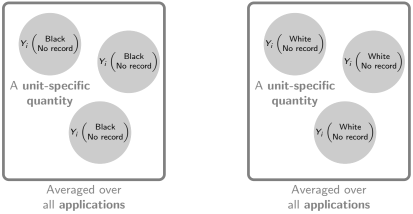
A **unit-specific quantity**

Y_i(No record)

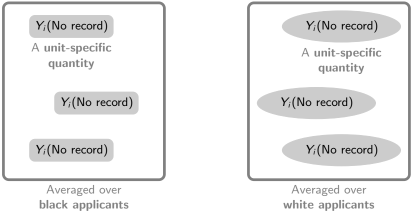
Y_i(No record)

Averaged over **white applicants**

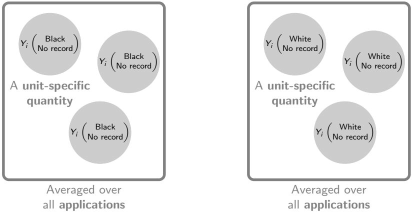
Estimand 1: Racial **discrimination**



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



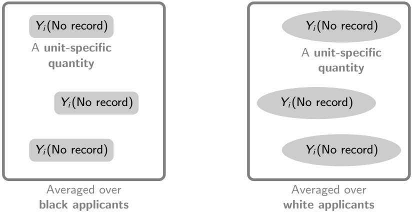
Estimand 1: Racial **discrimination**



Two treatment conditions

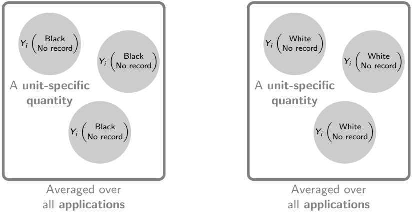
One population

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

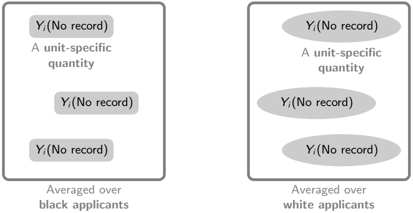
Estimand 1: Racial **discrimination**



Two treatment conditions

One population

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



One treatment condition

Two populations

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

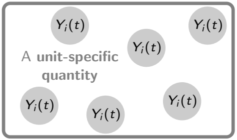
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

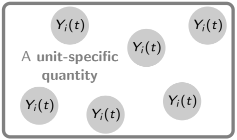
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

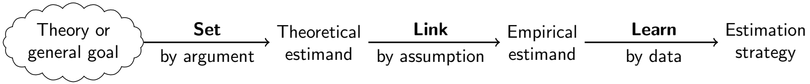
Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

Angrist and Evans 1998



Effect of motherhood
on employment

Angrist and Evans 1998

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

Effect of motherhood
on employment

First two births
are the same sex

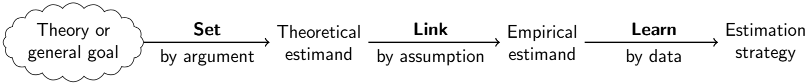
Angrist and Evans 1998

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

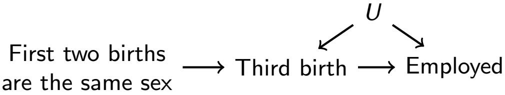
Effect of motherhood
on employment

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

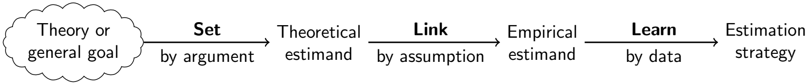
Angrist and Evans 1998



Effect of motherhood
on employment

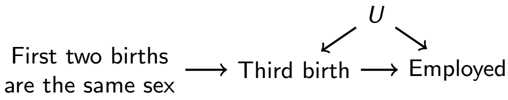


Angrist and Evans 1998



Vague estimand

Effect of motherhood
on employment



Angrist and Evans 1998

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

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

$$\begin{tikzcd}[column sep=large] \text{Theory or general goal} \arrow[r, "\textbf{Set}", "\text{by argument}"'] & \text{Theoretical estimand} \arrow[r, "\textbf{Link}", "\text{by assumption}"'] & \text{Empirical estimand} \arrow[r, "\textbf{Learn}", "\text{by data}"'] & \text{Estimation strategy} \end{tikzcd}$$

unit-specific quantity

Vague estimand

Effect of motherhood on employment

Precise estimand

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

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

Angrist and Evans 1998

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

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]

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

Angrist and Evans 1998

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

Precise estimand

Effect of having 3 vs. 2 children

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

$\approx$ 4% of all mothers

Angrist and Evans 1998

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

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

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

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

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

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) It speaks to some broader estimand

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

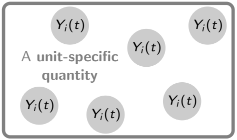
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

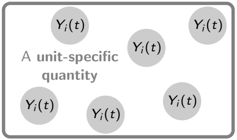
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

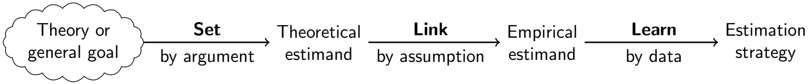
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



Example: Age-standardized mortality

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.

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

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.

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

Descriptive Estimand

Age-specific mortality
is descriptive

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

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Problem: Why adjust for 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.
3. Report the disparity between the two countries.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Problem: Why adjust for age?

Why not obesity,

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Problem: Why adjust for age?

Why not obesity, blood pressure,

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Problem: Why adjust for age?

Why not obesity, blood pressure, exercise,

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Problem: Why adjust for age?

Why not obesity, blood pressure, exercise, occupational hazards...

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Identified ✓

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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

Identified ✓

Meaningful ?

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.

Descriptive Estimand

Age-specific mortality is descriptive

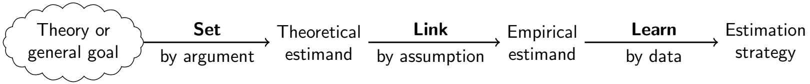
Aggregation is a simple summary

Causal Estimand

The “effect” of social context

Identified ✓

Meaningful ?



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.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand

The "effect" of social context

A "counterfactual" population

Identified ✓

Meaningful ?

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

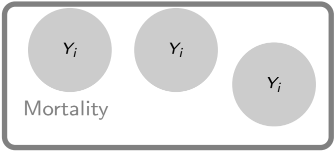
1. Estimate mortality in the U.S. and Mexico at each age.
2. Aggregate over the U.S. age distribution.
3. Report the disparity between the two countries.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand



Averaged over the U.S. population

Identified ✓

Meaningful ?

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

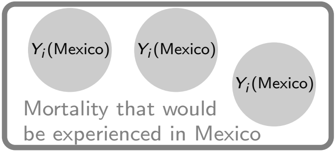
1. Estimate mortality in the U.S. and Mexico at each age.
2. Aggregate over the U.S. age distribution.
3. Report the disparity between the two countries.

Descriptive Estimand

Age-specific mortality is descriptive

Aggregation is a simple summary

Causal Estimand



Averaged over the U.S. population

Identified ✓

Meaningful ?

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.

Descriptive Estimand

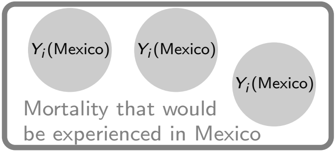
Age-specific mortality is descriptive

Aggregation is a simple summary

Identified ✓

Meaningful ?

Causal Estimand



Averaged over the U.S. population

Identified ✗

Lundberg, Johnson, and Stewart. What is Your 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.
2. Aggregate over the U.S. age distribution.
3. Report the disparity between the two countries.

Descriptive Estimand

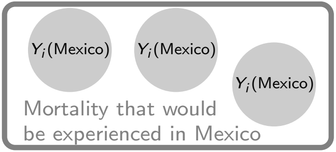
Age-specific mortality is descriptive

Aggregation is a simple summary

Identified ✓

Meaningful ?

Causal Estimand



Averaged over the U.S. population

Identified ✗

Meaningful ✓

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

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.

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

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

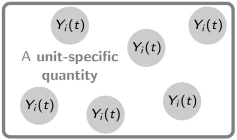
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

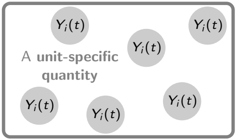
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

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)

I. 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 Bud Riley, and Chief Scott Thomson. I am grateful to David Card, Kerwin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Overdeck, Jesse Shapiro, Andrei Shleifer, Jorg Spenkuch, Max Stone, John Van Reenan, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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

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

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

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)

I. 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 Bud Riley, and Chief Scott Thomson. I am grateful to David Card, Kerwin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Overdeck, Jesse Shapiro, Andrei Shleifer, Jorg Spenkuch, Max Stone, John Van Reenan, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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

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

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

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)

I. 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 Bud Riley, and Chief Scott Thomson. I am grateful to David Card, Kerwin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Overdeck, Jesse Shapiro, Andrei Shleifer, Jorg Spenkuch, Max Stone, John Van Reenan, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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

1210

TheUpshot

DATA DIVE

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

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

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

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)

I. 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 Bud Riley, and Chief Scott Thomson. I am grateful to David Card, Kerwin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Overdeck, Jesse Shapiro, Andrei Shleifer, Jorg Spenkuch, Max Stone, John Van Reenan, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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


TheUpshot

DATA DIVE

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

OPINION | COMMENTARY

The Myth of Systemic Police Racism

WSJ | OPINION

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

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

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

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

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

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.

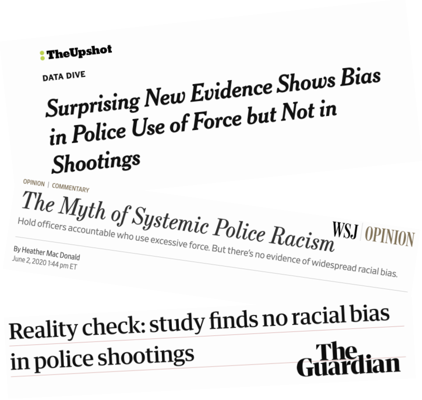
> We can never be satisfied as long as the Negro is the victim of the unspeakable horrors of police brutality. (Martin Luther King Jr., August 28, 1963)

I. 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 Bud Riley, and Chief Scott Thomson. I am grateful to David Card, Kerwin Charles, Christian Dustmann, Michael Greenstone, James Heckman, Richard Holden, Lawrence Katz, Steven Levitt, Jens Ludwig, Glenn Loury, Kevin Murphy, Derek Neal, John Overdeck, Jesse Shapiro, Andrei Shleifer, Jorg Spenkuch, Max Stone, John Van Reenan, Christopher Winship, and seminar participants at Brown University, University of Chicago, London

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



Lundberg, Johnson, and Stewart. What is Your 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

Evidence:

Claim:

Why wrong:

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

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim:

Why wrong:

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

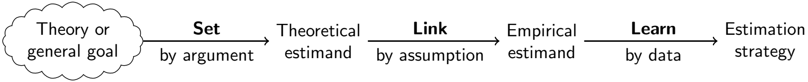
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim: Police are unbiased

Why wrong:

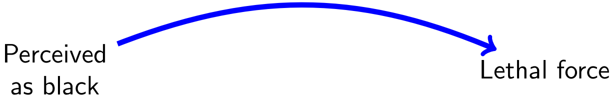
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



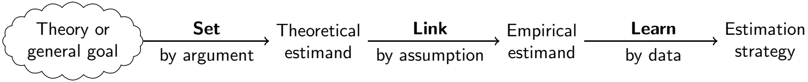
Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim: Police are unbiased

Why wrong:



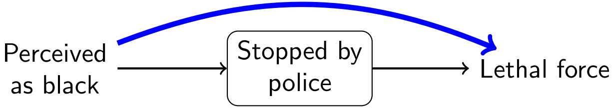
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



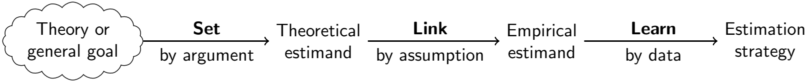
Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim: Police are unbiased

Why wrong:



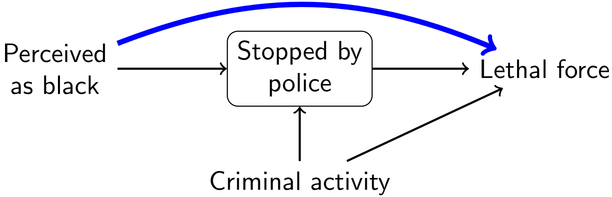
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



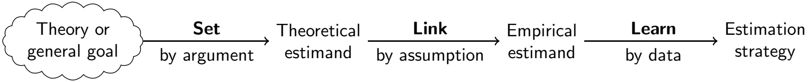
Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

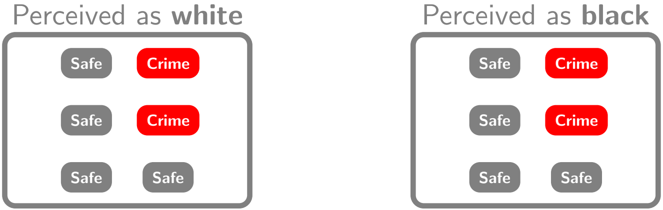
Claim: Police are unbiased

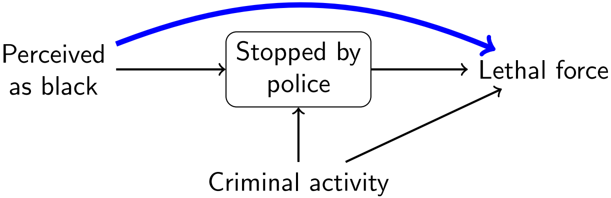
Why wrong:



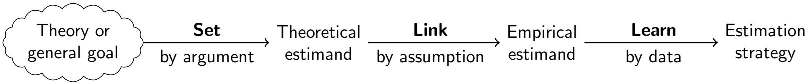
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.

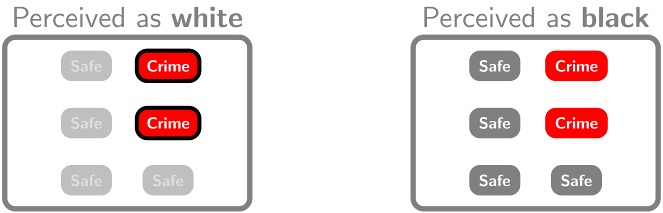


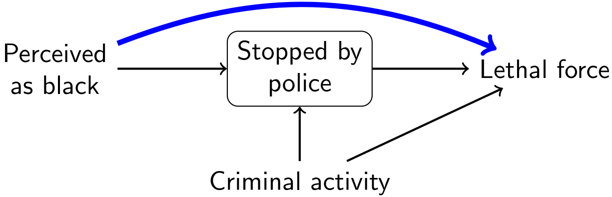




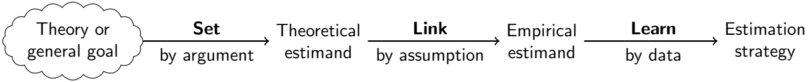
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.

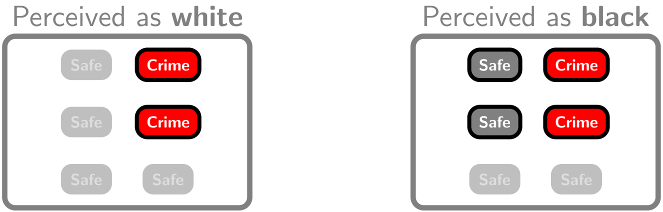


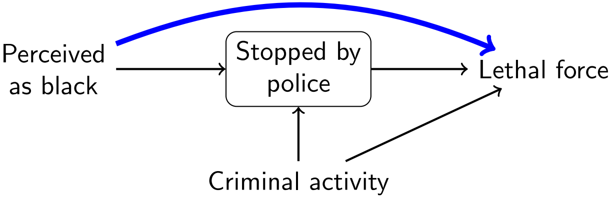




Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.







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

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim: Police are unbiased

Why wrong: Causal sample selection. Among those stopped, the white civilians may be more dangerous.

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

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

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

Claim: Police are unbiased

Why wrong: Causal sample selection. Among those stopped, the white civilians may be more dangerous.

Fryer responds:

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

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

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

~~**Claim:** Police are unbiased~~

Why wrong: Causal sample selection. Among those stopped, the white civilians may be more dangerous.

Fryer responds:

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

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

Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

~~**Claim:** Police are unbiased~~

Why wrong: Causal sample selection. Among those stopped, the white civilians may be more dangerous.

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.

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

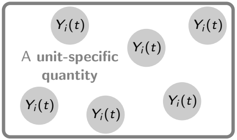
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

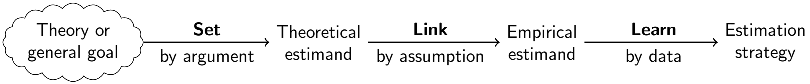
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

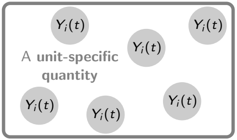
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

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

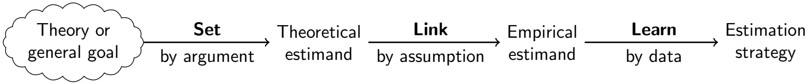
Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



Review

All 32 articles in ASR 2018 using quantitative data

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

Review
All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles | 56% of *ASR*
Causal target: Observational data

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

7 articles | 22% of *ASR*
Descriptive target

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

Review
All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles | 56% of *ASR*	7 articles | 22% of *ASR*	7 articles | 22% of *ASR*
Causal target: Observational data	Causal target: Experiments	Descriptive target
0 out of 18 articles was clear	**4 out of 7** articles were clear	**1 out of 7** articles was clear

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

Review
All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles · 56% of *ASR*	7 articles · 22% of *ASR*	7 articles · 22% of *ASR*
Causal target: Observational data	Causal target: Experiments	Descriptive target
0 out of 18 articles was clear	**4 out of 7** articles were clear	**1 out of 7** articles was clear

Clarity about the **target population**

3 types of articles with distinct issues

16 articles · 50% of *ASR*	6 articles · 19% of *ASR*	10 articles · 31% of *ASR*
Probability samples	Administrative records	Other samples

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

Review
All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

18 articles | 56% of *ASR*
Causal target: Observational data
0 out of 18
articles was clear

7 articles | 22% of *ASR*
Causal target: Experiments
4 out of 7
articles were clear

7 articles | 22% of *ASR*
Descriptive target
1 out of 7
articles was clear

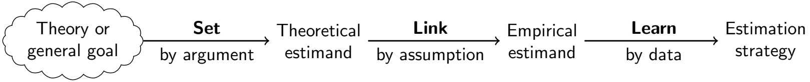
Clarity about the **target population**

3 types of articles with distinct issues

16 articles | 50% of *ASR*
Probability samples
6 out of 16
articles were clear

6 articles | 19% of *ASR*
Administrative records
1 out of 6
articles was clear

10 articles | 31% of *ASR*
Other samples
2 out of 10
articles were clear



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

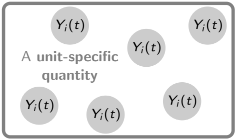
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

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

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

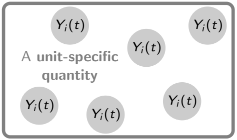
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

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

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

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.

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

Is the theoretical estimand descriptive?

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

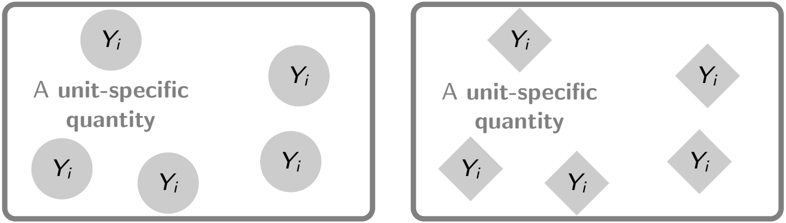
Is the theoretical estimand descriptive?

> “the differential in hourly wages
> between women with children
> and women without children”

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

Is the theoretical estimand descriptive?

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



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

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

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

Is the theoretical estimand descriptive? Is it causal?

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.

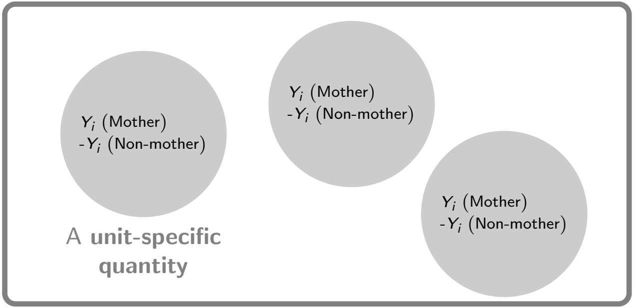
Is the theoretical estimand descriptive? Is it causal?

"causal estimation techniques"

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

Is the theoretical estimand descriptive? Is it causal?

"causal estimation techniques"

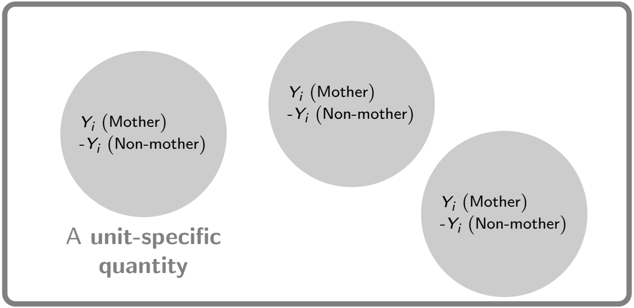


Averaged over a **target population** of **mothers**

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

Is the theoretical estimand descriptive? Is it causal?

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

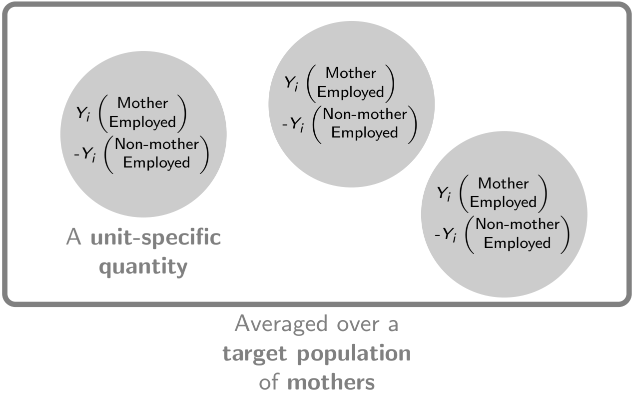


Averaged over a **target population** of **mothers**

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

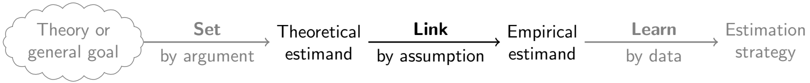
Is the theoretical estimand descriptive? Is it causal?

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

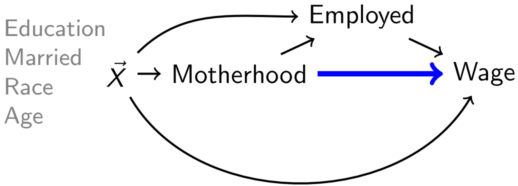


Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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

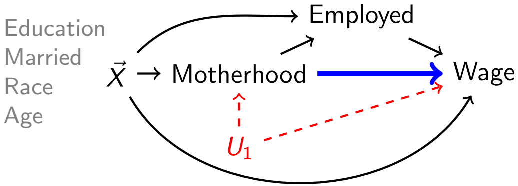


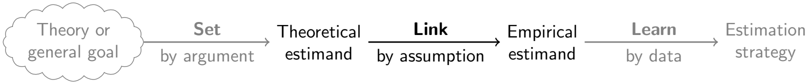
Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\\text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\\text{Employed}\end{pmatrix}$



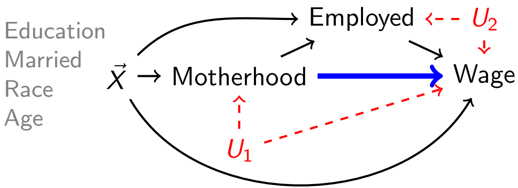
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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





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

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

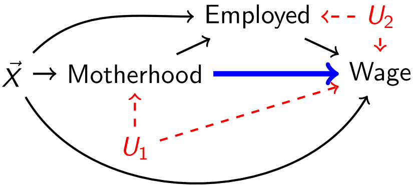
Potential outcomes

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

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

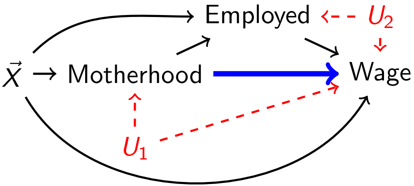
$Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$ $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix}$

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

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

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

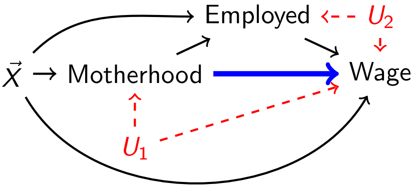
Potential outcomes

$Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$ $Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$ $Y_i\left(\begin{matrix}\text{Mother,}\\ \text{Employed}\end{matrix}\right)$

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

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

Education
Married
Race
Age



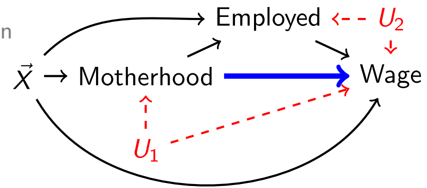
Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

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

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

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

Education
Married
Race
Age



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

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

Potential outcomes

$Y_i\left(\begin{array}{c}\text{Mother,}\\ \text{Employed}\end{array}\right)$ $Y_i\left(\begin{array}{c}\text{Mother,}\\ \text{Employed}\end{array}\right)$ $Y_i\left(\begin{array}{c}\text{Mother,}\\ \text{Employed}\end{array}\right)$

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

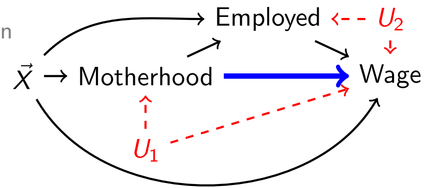
Realized outcomes

Y_i Y_i

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

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

Education
Married
Race
Age



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

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

Realized outcomes

Y_i

Y_i

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

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

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

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

Realized outcomes

Y_i

Y_i

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

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

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

Any prediction algorithm that minimizes squared errors

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

Realized outcomes

Y_i

Y_i

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

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

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

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

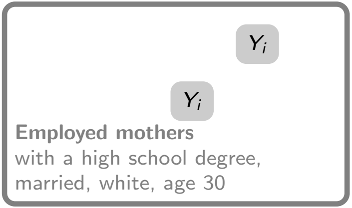
$\downarrow$

Any prediction algorithm that minimizes squared errors

$\downarrow$

Generalized Additive Model

Realized outcomes



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

Y_i

Y_i

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

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

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

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

Any prediction algorithm that minimizes squared errors

- 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

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

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

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

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

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

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

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

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

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

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

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	

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
	+ Include each age as a separate indicator variable
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 → **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	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

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

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	

	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	

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

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

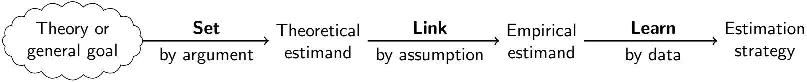
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
>
> — Buchmann and DiPrete 2006

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

Coefficient:
Gender × Cohort
× Father status

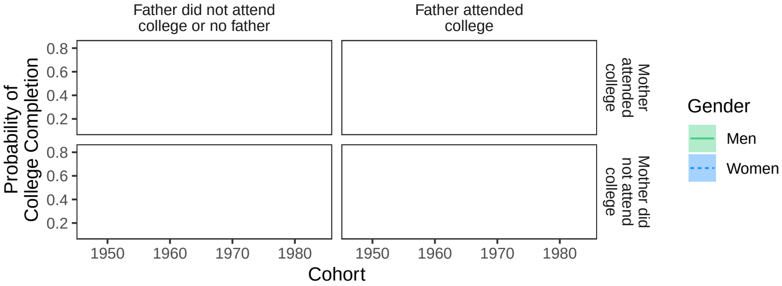
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
>
> — Buchmann and DiPrete 2006

Descriptive estimand: Proportion completing college within subgroups of the predictors



Coefficient:
Gender × Cohort
× Father status

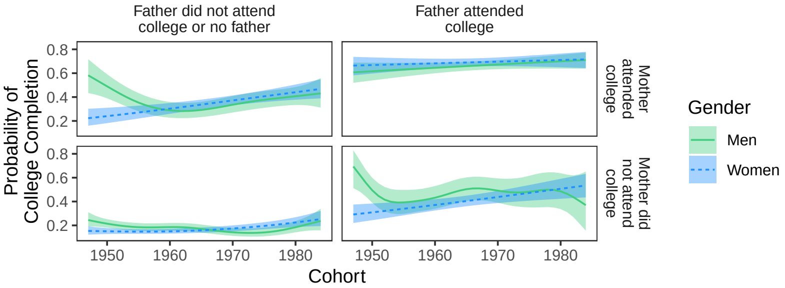
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006

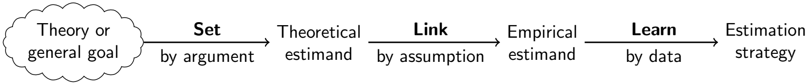


Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

Coefficient:
Gender × Cohort × Father status

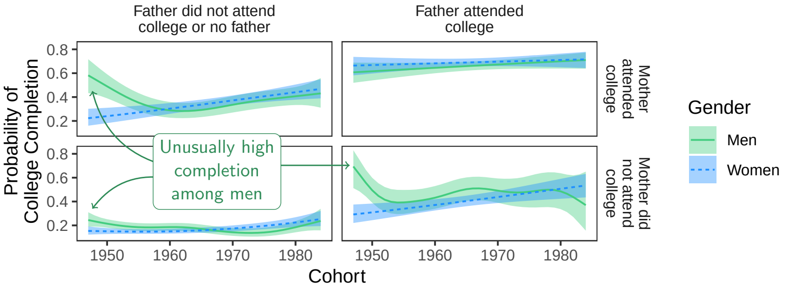
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006

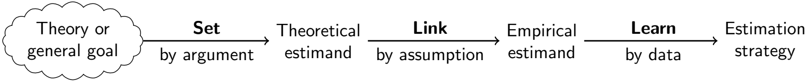




Coefficient:
Gender × Cohort
× Father status

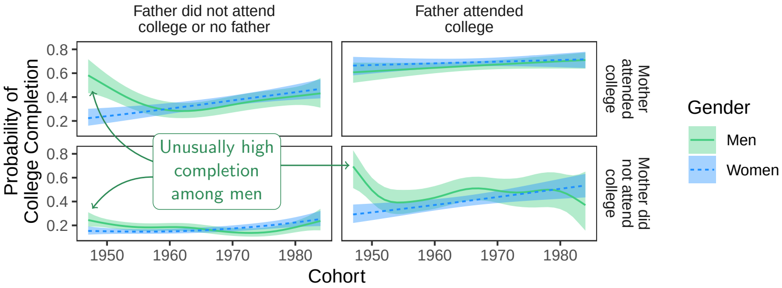
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006





Coefficient:
Gender × Cohort
× 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



Alternate theory: The Vietnam War

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

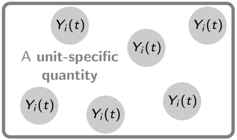
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

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

Extend to answer new theoretical questions

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

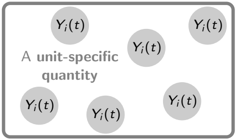
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

→ **Extend** to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

Lundberg, Ian
Working paper
On SocArxiv

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

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

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

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

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

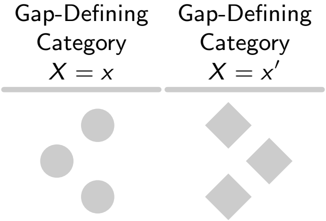
Question we ask $\xleftarrow{\textbf{constrain}}$ Familiar methods

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

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

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

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

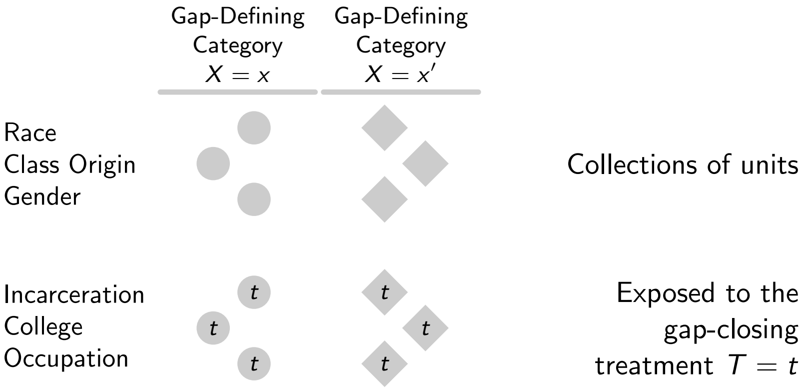


Race
Class Origin
Gender

Collections of units

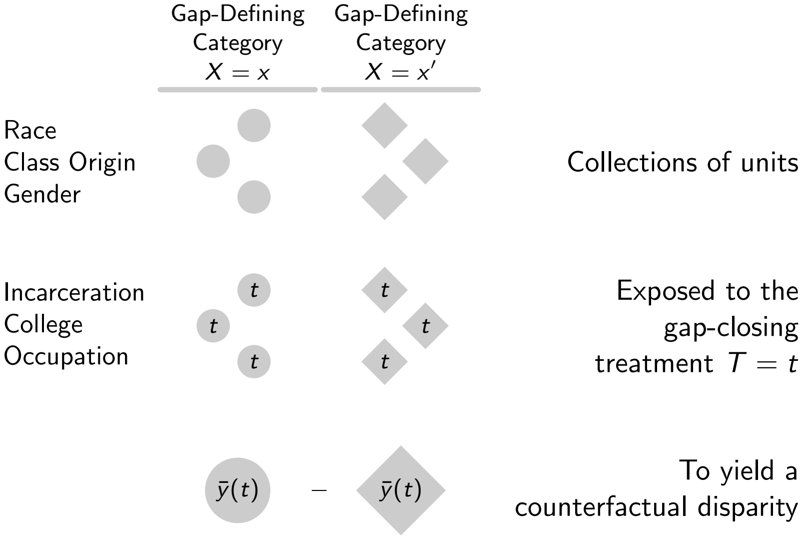
The Gap-Closing Estimand:
A Causal Approach to Study Interventions
That Close Disparities Across Social Categories

Lundberg, Ian
Working paper
On SocArxiv



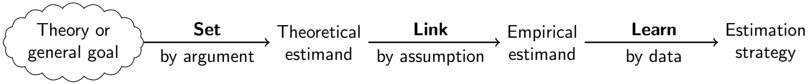
The Gap-Closing Estimand:
A Causal Approach to Study Interventions That Close Disparities Across Social Categories

Lundberg, Ian
Working paper
On SocArxiv



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

Lundberg, Ian
Working paper
On SocArxiv



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

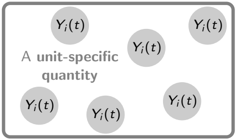
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

→ **Extend** to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

Illustrate through four examples. We have to:

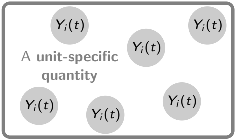
1) Distinguish causal treatments from population labels
2) Recognize when empirical evidence is narrow
3) Address ambiguity about descriptive and causal claims
4) Beware of causal selection in descriptive claims

Document widespread vagueness in *ASR*

Replicate studies to demonstrate the framework in action

Extend to answer new theoretical questions

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

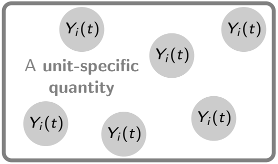


Averaged over a **target population**

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

What is your estimand?

⟵ Every quantitative study should answer this question



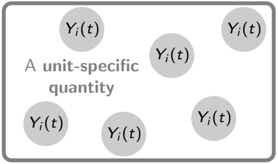
Averaged over a **target population**

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

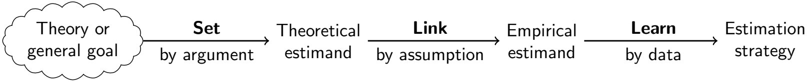
What is your estimand?

← Every quantitative study should answer this question

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



Averaged over a **target population**

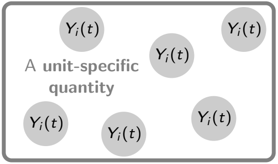


What is your estimand?

⟵ Every quantitative study should answer this question

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

— Motivate the question outside the model



Averaged over a **target population**

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

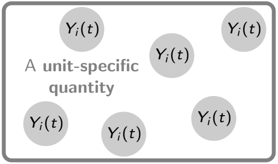
What is your estimand?

⟵ Every quantitative study should answer this question

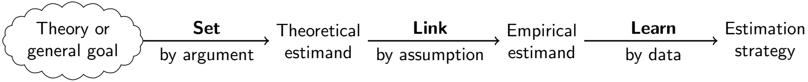
When you **write** a quantitative paper, the estimand allows you to

— Motivate the question outside the model

— Address selection transparently



Averaged over a **target population**



What is your estimand?

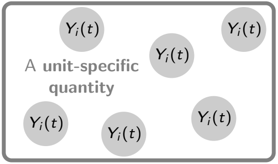
⟵ Every quantitative study should answer this question

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

— Motivate the question outside the model

— Address selection transparently

— Unlock computational tools



Averaged over a **target population**

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

What is your estimand?

⟵ Every quantitative study should answer this question

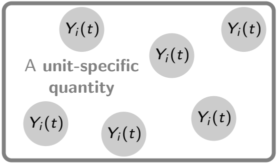
When you **write** a quantitative paper, the estimand allows you to

— Motivate the question outside the model

— Address selection transparently

— Unlock computational tools

— Present interpretable summaries



Averaged over a **target population**

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

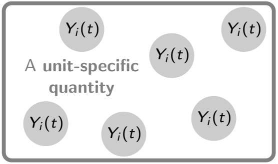
What is your estimand?

⟵ Every quantitative study should answer this question

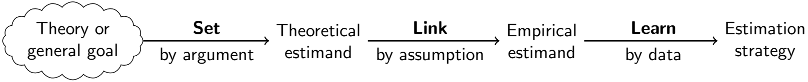
When you **read** a quantitative paper, the estimand allows you to

— Understand the author's aim

— Pinpoint your concerns



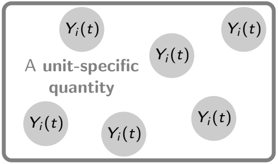
Averaged over a **target population**



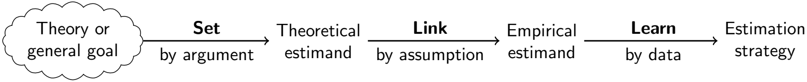
What is your estimand?

⟵ Every quantitative study should answer this question

In the future, estimands will only become more important



Averaged over a **target population**



What is your estimand?

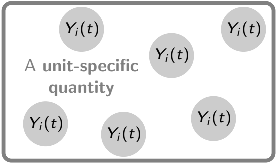
⟵ Every quantitative study should answer this question

In the future, estimands will only become more important

New data have missing values

— Non-probability samples

— Administrative records



Averaged over a **target population**

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

What is your estimand?

⟵ Every quantitative study should answer this question

In the future, estimands will only become more important

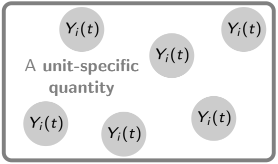
New data have missing values

— Non-probability samples

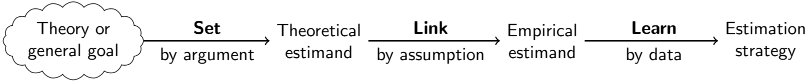
— Administrative records

New methods flourish with a clear goal

— Machine learning



Averaged over a **target population**



What is your estimand?

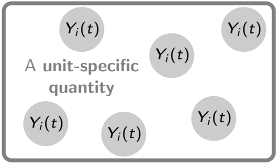
⟵ Every quantitative study should answer this question

In the future, estimands will only become more important

New data have missing values

— Non-probability samples

— Administrative records



Averaged over a **target population**

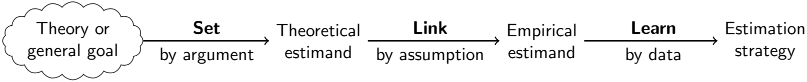
New methods flourish with a clear goal

— 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

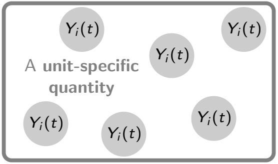
ilundberg at princeton dot edu
ianlundberg.org

Rebecca Johnson

rebecca.ann.johnson at dartmouth dot edu
rebeccajohnson.io

Brandon Stewart

bms4 at princeton dot edu
brandonstewart.org



Averaged over a **target population**

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