What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Ian Lundberg
UCLA
Sociology
ianlundberg.org

Rebecca Johnson
Dartmouth Quantitative
Social Science
rebeccajohnson.io

Brandon M. Stewart
Princeton
Sociology
brandonstewart.org

23 September 2021.
Paper in *American Sociological Review*. Preprint 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

$$Y = \beta_0 + X_1 \underset{\substack{\uparrow \\ \beta_1 \text{ is an estimand} \\ \text{that assumes a model}}}{\beta_1} + X_2\beta_2 + \epsilon$$

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

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

$$Y = \beta_0 + X_1 \underset{\substack{\uparrow \\ \beta_1 \text{ is an estimand} \\ \text{that assumes a model}}}{\beta_1} + X_2\beta_2 + \epsilon$$

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

$Y_i(t)$

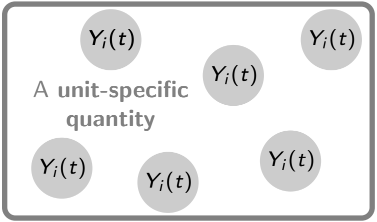
A **unit-specific quantity**

There is a question every quantitative study must answer:

What is your estimand?

The **purpose** of the statistical analysis

stated **outside** of the model



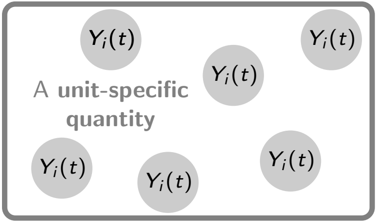
Aggregated over a **target population**

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**,

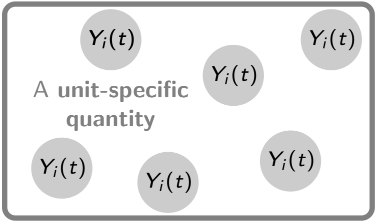
and unlocks computational **tools**

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**,

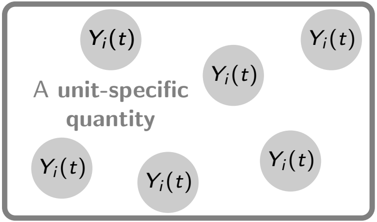
and unlocks computational **tools**

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**,

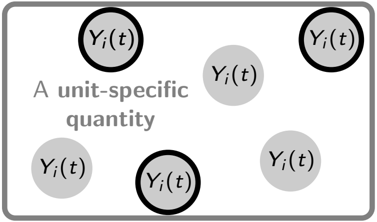
and unlocks computational **tools**

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**,

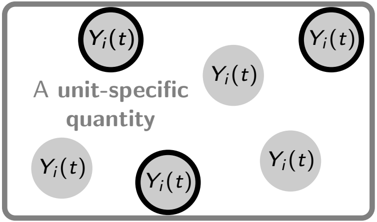
and unlocks computational **tools**

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**,

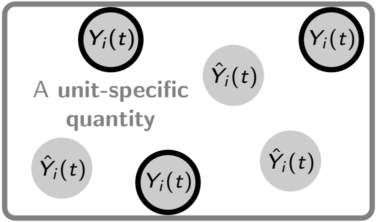
and unlocks computational **tools**

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

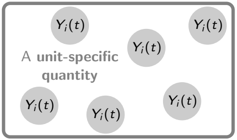
Illustrate through three examples where something went wrong

Document that these issues are everywhere

Demonstrate how our framework can help

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

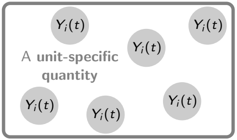
Illustrate through three examples where something went wrong

Document that these issues are everywhere

Demonstrate how our framework can help

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand

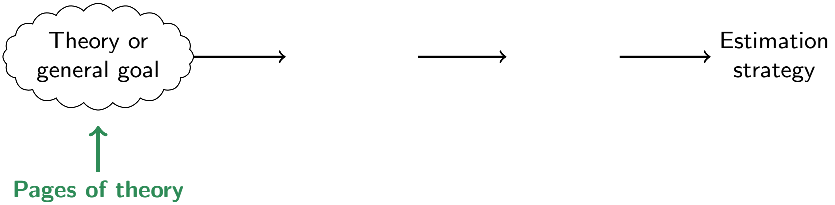


Averaged over a **target population**

Research framework: Estimands connect theory to evidence

Theory or general goal $\longrightarrow$ $\longrightarrow$ $\longrightarrow$ Estimation strategy

Research framework: Estimands connect theory to evidence



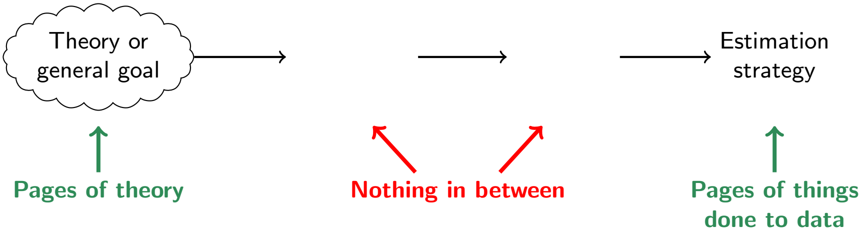
Research framework: Estimands connect theory to evidence

Theory or general goal ⟶ ⟶ ⟶ Estimation strategy

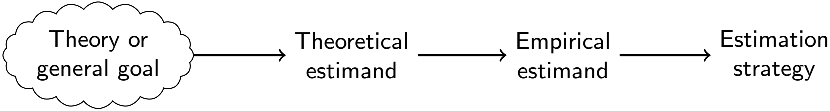
↑ **Pages of theory**

↑ **Pages of things done to data**

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 → Theoretical estimand → Empirical estimand → Estimation strategy

↑

Set
a specific
target

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 → Theoretical estimand → Empirical estimand → Estimation strategy

Set a specific target

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

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**	$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \Big(\underbrace{\text{Employed}_i(\text{Job training})}_{\text{Employment if received job training}} - \underbrace{\text{Employed}_i(\text{No job training})}_{\text{Employment if did not receive job training}} \Big)$

Research framework: Estimands connect theory to evidence

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

↑

Set
a specific
target

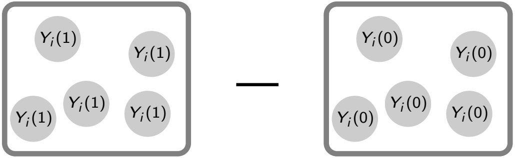
Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$$\frac{1}{\text{Size of U.S. adult population}} \sum_{\substack{i \text{ in U.S.} \\ \text{adult population}}} \Bigg(\underbrace{\text{Employed}_i(\text{Job training})}_{\substack{\text{Employment if received} \\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

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

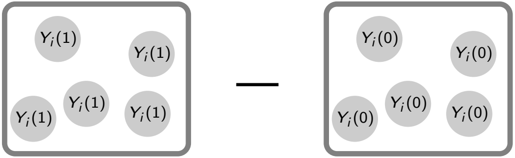
Lieberson 1987, Abbott 1988, Freedman 1991, Xie 2013, Hernán 2018

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

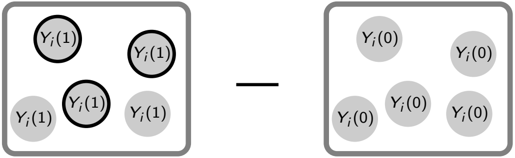
Definition	Example
A quantity involving **observable data**	

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

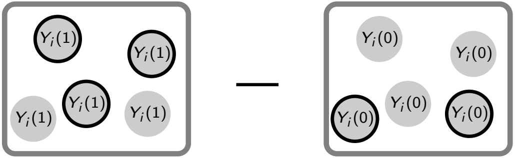
Definition	Example
A quantity involving **observable data**	

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**	

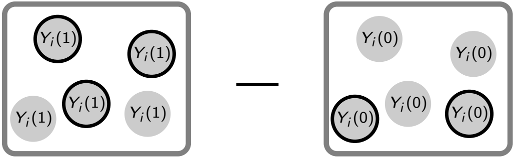
Research framework: Estimands connect theory to evidence

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**	



$$\begin{tikzcd} \vec{X} \arrow[r] \arrow[rr, bend right] & T \arrow[r] & Y \end{tikzcd}$$

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

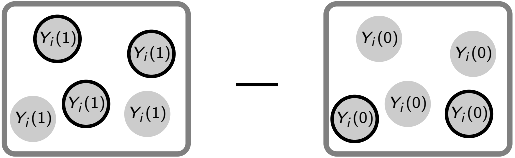
Research framework: Estimands connect theory to evidence

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

Set a specific target

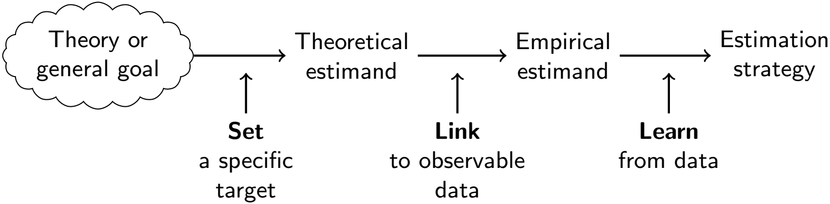
Link to observable data

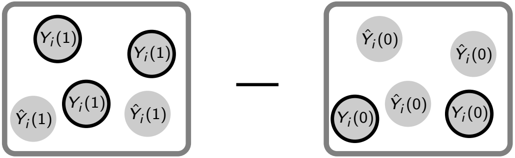
Learn from data

Definition	Example
An algorithm applied to data	

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

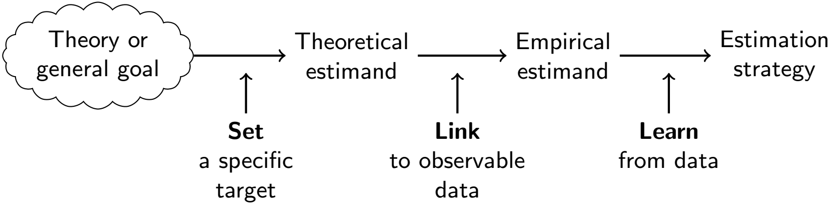
Research framework: Estimands connect theory to evidence



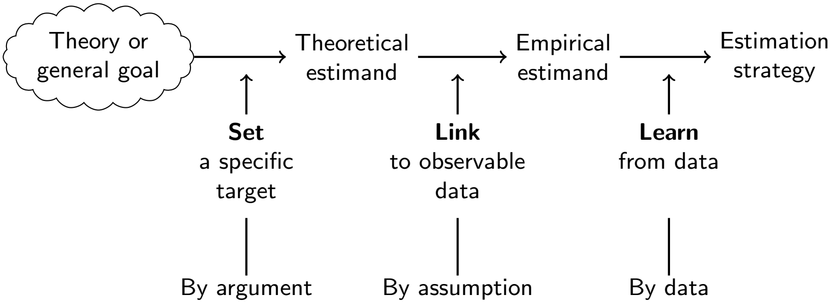
Definition	Example
An algorithm applied to data	

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

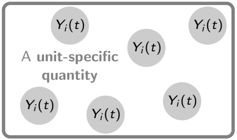
Illustrate through three examples where something went wrong

Document that these issues are everywhere

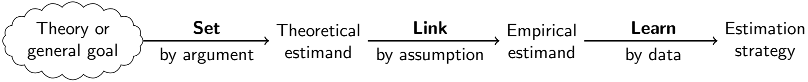
Demonstrate how our framework can help

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

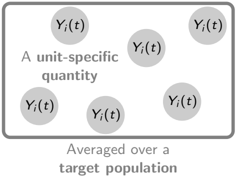
→ **Illustrate** through three examples where something went wrong

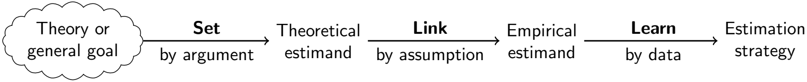
Document that these issues are everywhere

Demonstrate how our framework can help

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand





Example 1: An influential study with a **narrow theoretical 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

Angrist and Evans 1998

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

Effect of motherhood
on employment

Angrist and Evans 1998

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

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

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

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

Angrist and Evans 1998

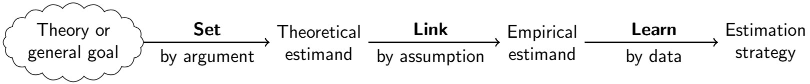
$$\begin{tikzcd}[column sep=large] \text{Theory or general goal} \arrow[r, "\textbf{Set}", "\text{by argument}"'] & \text{Theoretical estimand} \arrow[r, "\textbf{Link}", "\text{by assumption}"'] & \text{Empirical estimand} \arrow[r, "\textbf{Learn}", "\text{by data}"'] & \text{Estimation strategy} \end{tikzcd}$$

Vague estimand

Effect of motherhood on employment

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

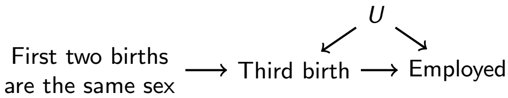
Angrist and Evans 1998



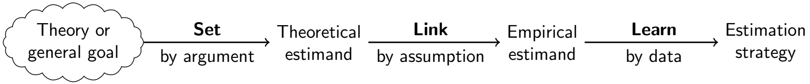
Vague estimand

Effect of motherhood
on employment

Precise estimand



Angrist and Evans 1998



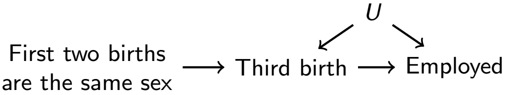
unit-specific quantity

Vague estimand

Effect of motherhood on employment

Precise estimand

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



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

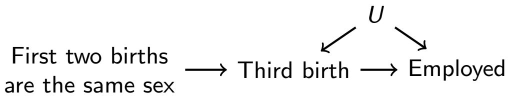
Effect of motherhood on employment

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]



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

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 for one of two things:

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

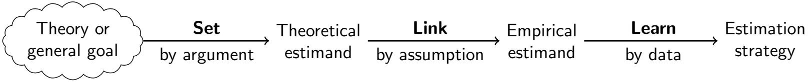
$\approx$ 4% of all mothers

You have to argue for one of two things:

1) That estimand matters for theory, or

2)

Angrist and Evans 1998



Precise estimand

Effect of having 3 vs. 2 children

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

$\approx$ 4% of all mothers

You have to argue for one of two things:

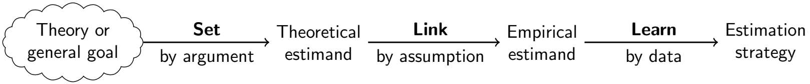
1) That estimand matters for theory, or

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

Example 2: An influential study with a misleading **link to evidence**



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]

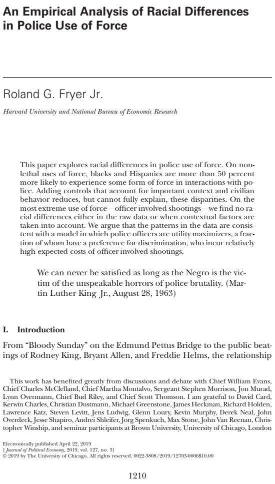
TheUpshot

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]
© 2019 by The University of Chicago. All rights reserved. 0022-3808/2019/12703-0006$10.00

1210


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

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

OPINION | COMMENTARY

The Myth of Systemic Police Racism

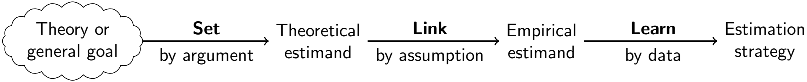
Hold officers accountable who use excessive force. But there's no evidence of widespread racial bias.

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

WSJ | OPINION

Reality check: study finds no racial bias in police shootings

The Guardian



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

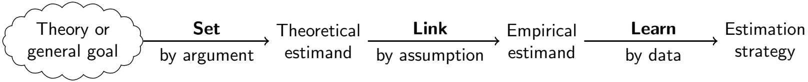
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.

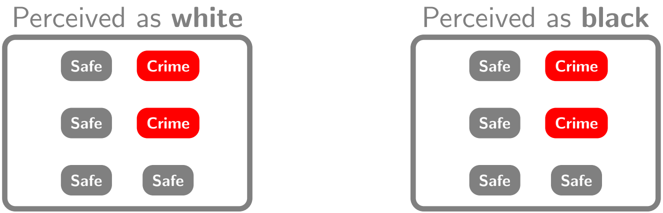
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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

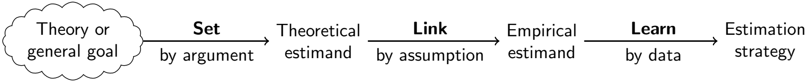
Claim: Police are unbiased

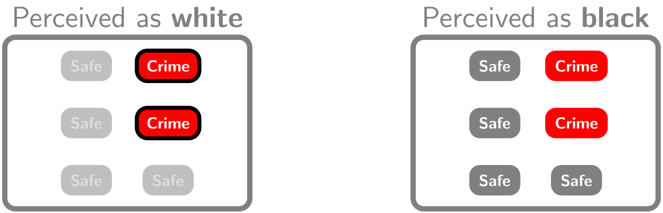
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



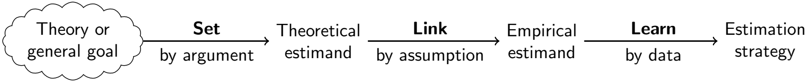


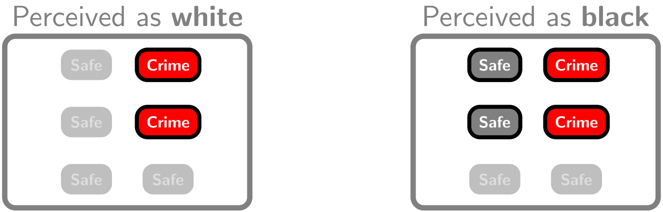
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.



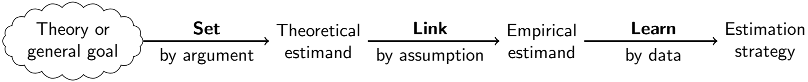


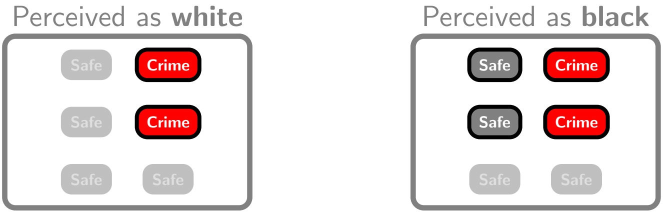
Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.

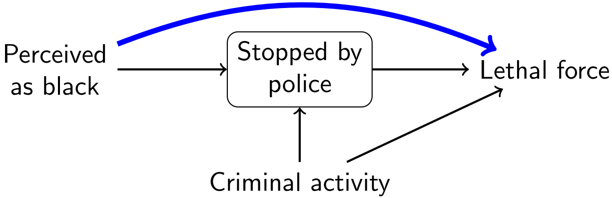




Fryer 2019. Fuller critique by Knox et al. 2020 and Durlauf and Heckman 2020.







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

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

Fryer responds:

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~~

Fryer responds:

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

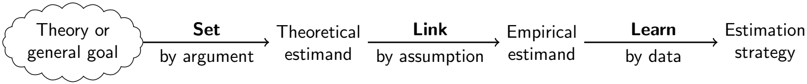
Evidence: Police use lethal force at the same rate against black and white civilians who are stopped.

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

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.



Example 3: An influential study where **estimation** led to confusion

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

> 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

	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

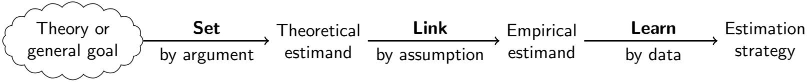
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
>
> — Buchmann and DiPrete 2006

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 $\times$ Cohort
$\times$ Father status

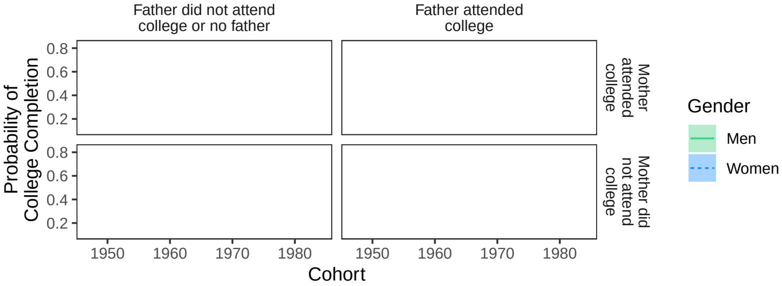
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006

Descriptive estimand: Proportion completing college within subgroups of the predictors



Coefficient:
Gender × Cohort
× Father status

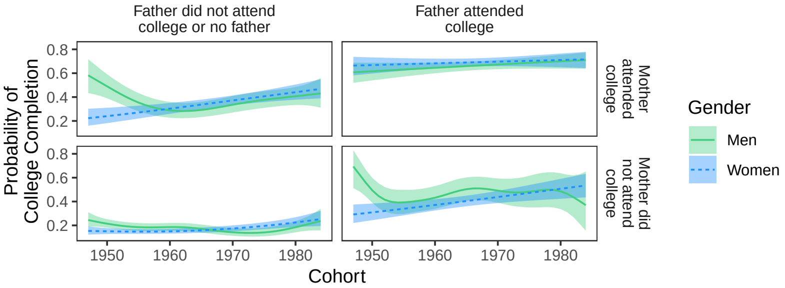
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006



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

Coefficient:
Gender × Cohort
× Father status

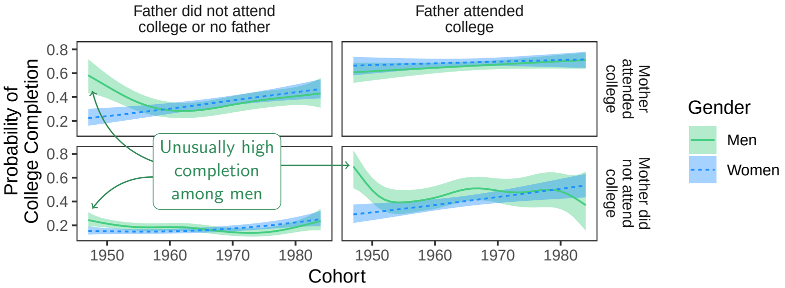
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006

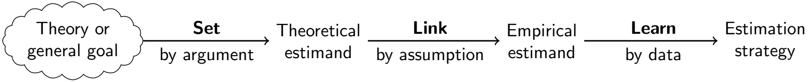


Theory or general goal → **Set** by argument → Theoretical estimand → **Link** by assumption → Empirical estimand → **Learn** by data → Estimation strategy

Coefficient:
Gender × Cohort
× Father status

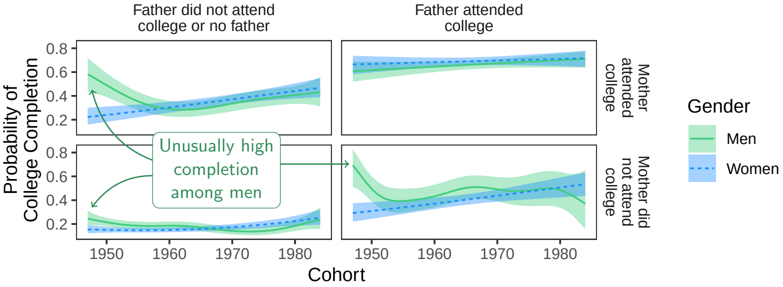
> The emergence of a female advantage in education is attributable to a reversal in the gender-specific effects of father status.
> — Buchmann and DiPrete 2006





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



Alternate theory: The Vietnam War

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

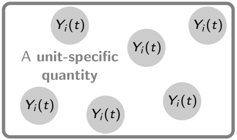
→ **Illustrate** through three examples where something went wrong

Document that these issues are everywhere

Demonstrate how our framework can help

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

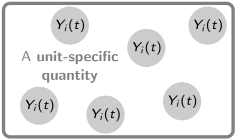
Illustrate through three examples where something went wrong

→ **Document** that these issues are everywhere

Demonstrate how our framework can help

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

Review

All 32 articles in ASR 2018 using quantitative data

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

Review

All 32 articles in ASR 2018 using quantitative data

Clarity about **unit-specific quantity**

3 types of articles with distinct issues

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

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

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

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

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*	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
6 out of 16 articles were clear	**1 out of 6** articles was clear	**2 out of 10** articles were clear

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

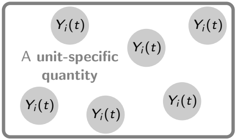
Illustrate through three examples where something went wrong

→ **Document** that these issues are everywhere

Demonstrate how our framework can help

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

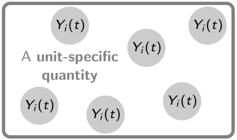
Illustrate through three examples where something went wrong

Document that these issues are everywhere

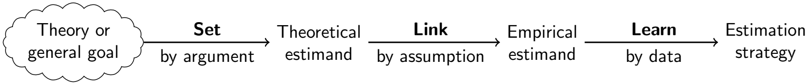
→ **Demonstrate** how our framework can help

Extend to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**



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

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

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

Is the theoretical estimand descriptive?

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

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

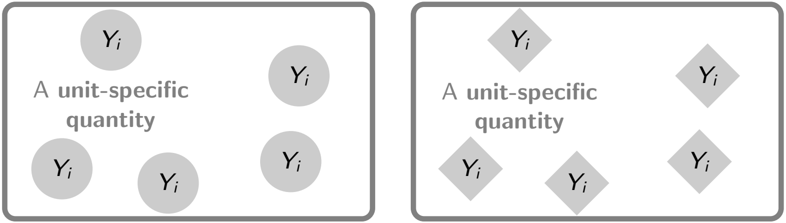
Is the theoretical estimand descriptive?

> "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**

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?

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?

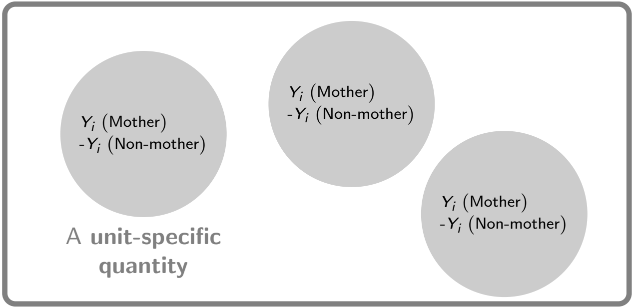
"causal estimation techniques"

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

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

Is the theoretical estimand descriptive? Is it causal?

"causal estimation techniques"

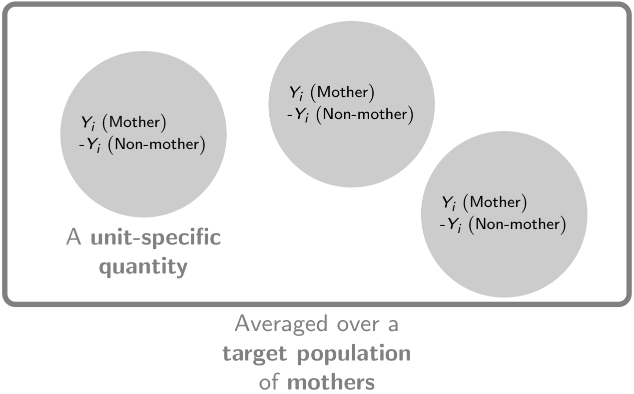


Averaged over a **target population** of **mothers**

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

Is the theoretical estimand descriptive? Is it causal?

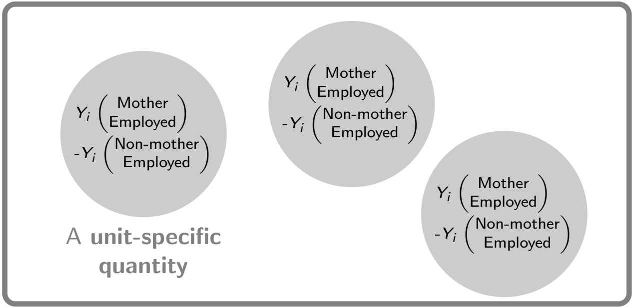
Added complexity: Wages are undefined for the non-employed.



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.



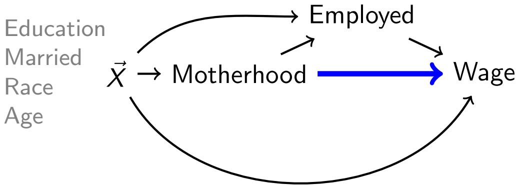
Averaged over a **target population** of **mothers**

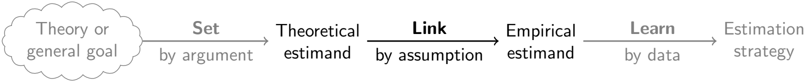
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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

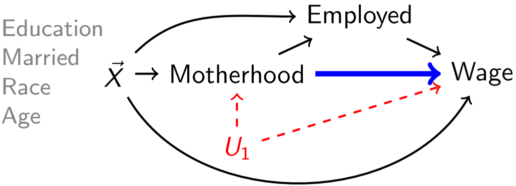
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

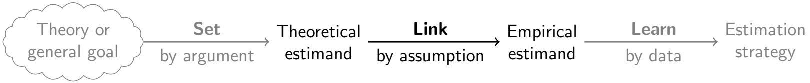
Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\ \text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\ \text{Employed}\end{pmatrix}$



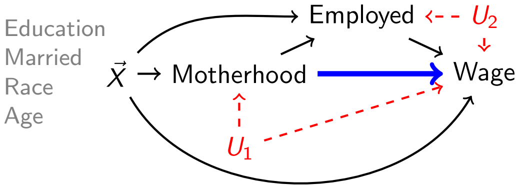


Unit-specific quantity: $Y_i\begin{pmatrix}\text{Mother,}\\\text{Employed}\end{pmatrix} - Y_i\begin{pmatrix}\text{Non-mother,}\\\text{Employed}\end{pmatrix}$





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

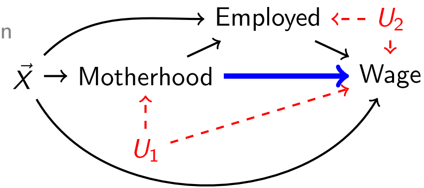
Potential outcomes

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

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

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

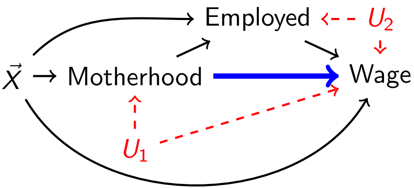
Potential outcomes

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

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

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

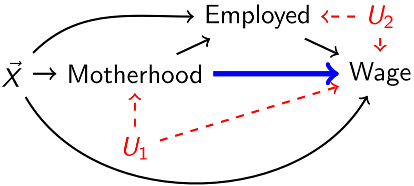
Potential outcomes

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

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

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

Potential outcomes

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

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

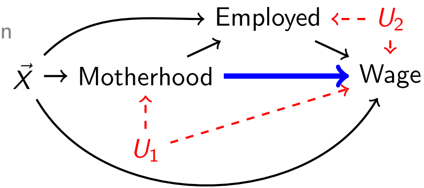
Realized outcomes

Y_i Y_i

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

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

Education
Married
Race
Age



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

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

Potential outcomes

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

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

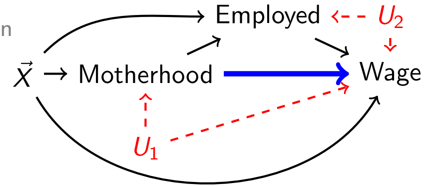
Realized outcomes

Y_i Y_i

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

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

Education
Married
Race
Age



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

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

Realized outcomes

Y_i

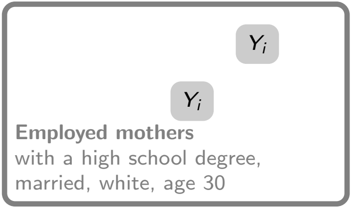
Y_i

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

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

This can be estimated by **machine learning**! $\longrightarrow$ $$\text{E}\left(Y_i \,\middle|\, \begin{array}{lcr} \text{Motherhood} & = & \text{Mother,} \\ \text{Employment} & = & \text{Employed,} \\ \text{Covariates } \vec{X} & = & \text{Observed } \vec{x}_i \end{array}\right)$$

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**!

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**!

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

Any prediction algorithm that minimizes squared errors

Generalized Additive Model

Realized outcomes

Y_i

Y_i

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

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

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

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

Any prediction algorithm that minimizes squared errors

Generalized Additive Model

Random Forest

Realized outcomes

Y_i

Y_i

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

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

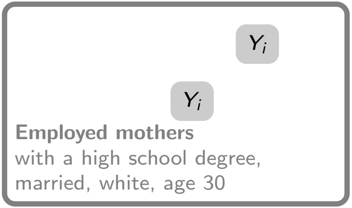
This can be estimated by **machine learning**! ⟶

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

Any prediction algorithm that minimizes squared errors

- Ordinary Least Squares
- Generalized Additive Model
- Random Forest

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

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

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

1) Learn an algorithm to predict the outcome

2) Predict for every unit at each treatment value

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

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

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

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

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

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

3) Average over the target population

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

This is called an **imputation estimator**

Hahn, 1998

Abadie & Imbens 2006

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

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

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Choose an algorithm by **predictive performance**

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

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

Most flexible

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

Least flexible

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

Most flexible

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

Least flexible

OLS with a quadratic for age

+ Interaction between age and motherhood

+ Allow a smooth curve for age rather than quadratic

+ Include each age as a separate indicator variable

Most flexible

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

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

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

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

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

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

Choose an algorithm by **predictive performance**

Outcome Log hourly wage

Predictors Motherhood, age, race, education, marital status

Candidate algorithms

Least flexible	OLS with a quadratic for age
Best predictions	+ Interaction between age and motherhood
	+ Allow a smooth curve for age rather than quadratic
	+ Include each age as a separate indicator variable
Most flexible	+ Include all interactions among all predictors

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

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**

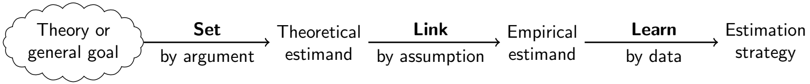
— What question is important? — theoretical estimand

— 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?



What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

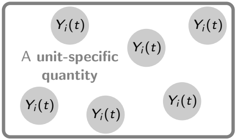
Illustrate through three examples where something went wrong

Document that these issues are everywhere

→ **Demonstrate** how our framework can help

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

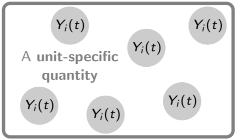
Illustrate through three examples where something went wrong

Document that these issues are everywhere

Demonstrate how our framework can help

→ **Extend** to answer new theoretical questions

Discuss Every quantitative study should define the estimand



Averaged over a **target population**

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?

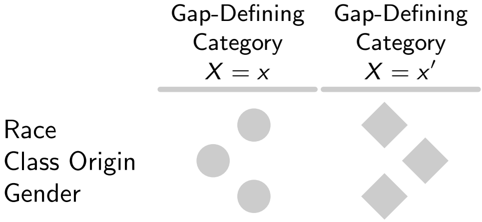
Question we ask ←**constrain**— Familiar methods

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

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

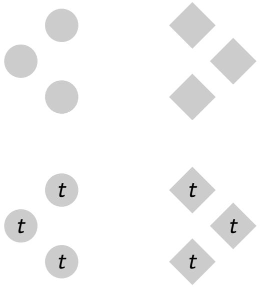
Question we ask $\xleftarrow{\text{constrain}}$ Familiar methods

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



Collections of units

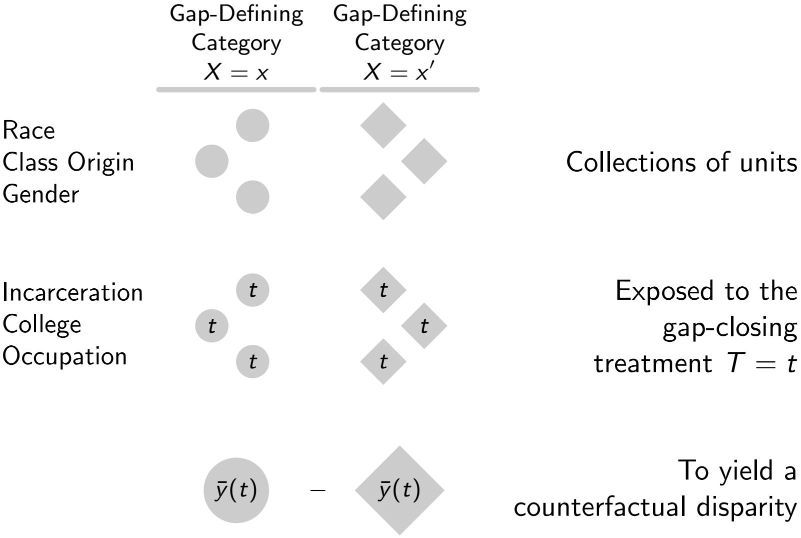
	Gap-Defining Category $X = x$	Gap-Defining Category $X = x'$	
Race Class Origin Gender			Collections of units
Incarceration College Occupation			Exposed to the gap-closing treatment $T = t$



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

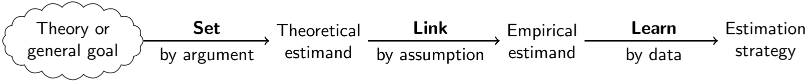
Lundberg, Ian

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

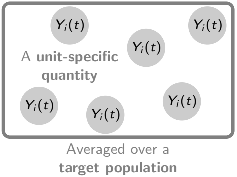
Illustrate through three examples where something went wrong

Document that these issues are everywhere

Demonstrate how our framework can help

→ **Extend** to answer new theoretical questions

Discuss Every quantitative study should define the estimand



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

What is Your Estimand?

Defining the Target Quantity Connects Statistical Evidence to Theory

Introduce a framework for quantitative social science

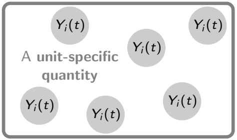
Illustrate through three examples where something went wrong

Document that these issues are everywhere

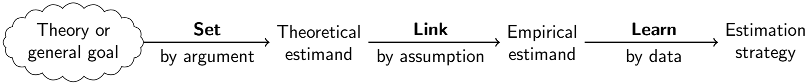
Demonstrate how our framework can help

Extend to answer new theoretical questions

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

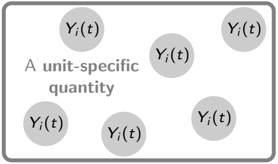


Averaged over a **target population**



What is your estimand?

⟵ Every quantitative study should answer this question



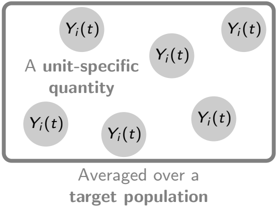
Averaged over a **target population**

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?

$\longleftarrow$ Every quantitative study should answer this question

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



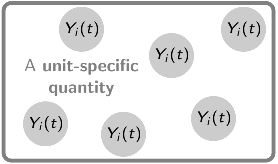
Theory or general goal $\xrightarrow[\text{by argument}]{\textbf{Set}}$ Theoretical estimand $\xrightarrow[\text{by assumption}]{\textbf{Link}}$ Empirical estimand $\xrightarrow[\text{by data}]{\textbf{Learn}}$ Estimation strategy

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



Averaged over a **target population**

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

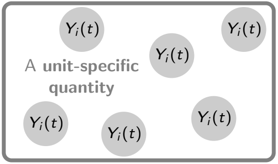
What is your estimand?

⟵ Every quantitative study should answer this question

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

— Motivate the question

— Address selection



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?

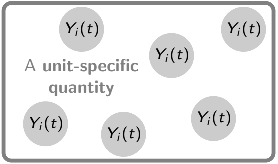
⟵ Every quantitative study should answer this question

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

— Motivate the question

— Address selection

— 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

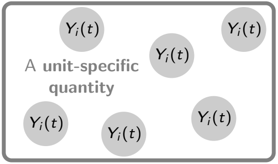
When you **write** a quantitative paper, the estimand allows you to

— Motivate the question

— Address selection

— Unlock computational tools

— Speak to a broad audience



Averaged over a **target population**

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

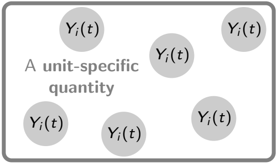
What is your estimand?

⟵ Every quantitative study should answer this question

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

— Understand the author's aim

— Pinpoint your concerns



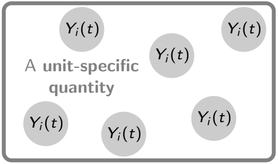
Averaged over a **target population**

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?

$\longleftarrow$ Every quantitative study should answer this question

In the future, estimands will only become more important



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?

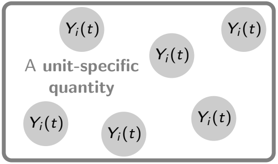
⟵ Every quantitative study should answer this question

In the future, estimands will only become more important

New data have missing values

— Non-probability samples

— Administrative records



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

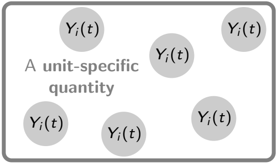
New data have missing values

— Non-probability samples

— Administrative records

New methods flourish with a clear goal

— Machine learning



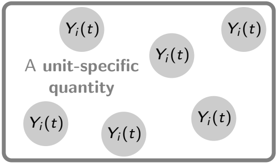
Averaged over a **target population**

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



Averaged over a **target population**

New data have missing values

— Non-probability samples

— Administrative records

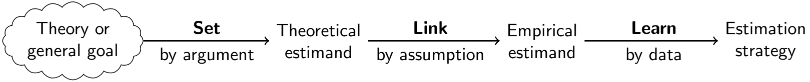
New methods flourish with a clear goal

— Machine learning

New questions can be found beyond coefficients

— Describe counterfactual disparities

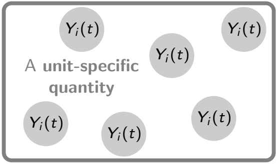
— Predict the effects of targeted interventions



What is your estimand?

⟵ Every quantitative study should answer this question

Defining the Target Quantity Connects Statistical Evidence to Theory



Averaged over a **target population**

Ian Lundberg

ilundberg@princeton.edu
ianlundberg.org

Rebecca Johnson

rebecca.ann.johnson@dartmouth.edu
rebeccajohnson.io

Brandon Stewart

bms4@princeton.edu
brandonstewart.org

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