Setting the Target

Precise Estimands and the Gap Between Theory and Empirics

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State of the field: How methods are used in sociology

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"[Variables] empirically perform as theoretically predicted,

Lundberg, Johnson, and Stewart. Setting the Target: Precise Estimands and the Gap Between Theory and Empirics

State of the field: How methods are used in sociology

"[Variables] empirically perform as theoretically predicted,
by displaying statistically significant
effects net of other variables in the right direction"

Lundberg, Johnson, and Stewart. Setting the Target: Precise Estimands and the Gap Between Theory and Empirics

The **target tautology**:

Research goals are defined by hypotheses about model coefficients

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Solution:

State the research goal
separately from the estimation strategy

The **target tautology**:

Research goals are defined by hypotheses about model coefficients

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The goal is only defined within the statistical model

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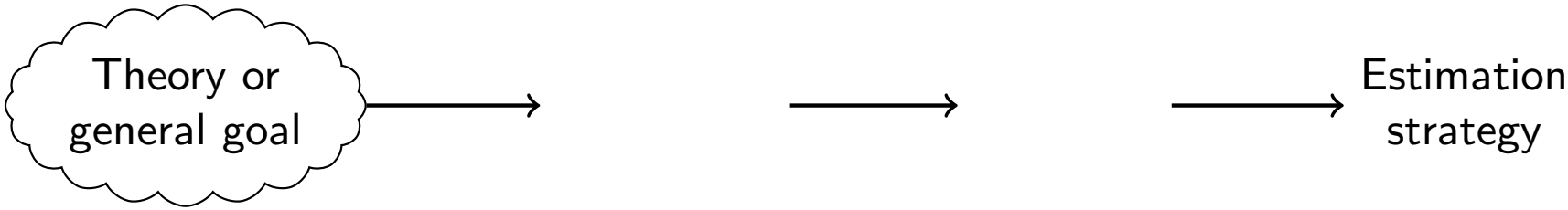
It becomes impossible to reason about other estimation strategies

Solution:

Our **diagnosis** for the source of many methodological problems

State the research goal separately from the estimation strategy

Our solution: A framework centered on **estimands**



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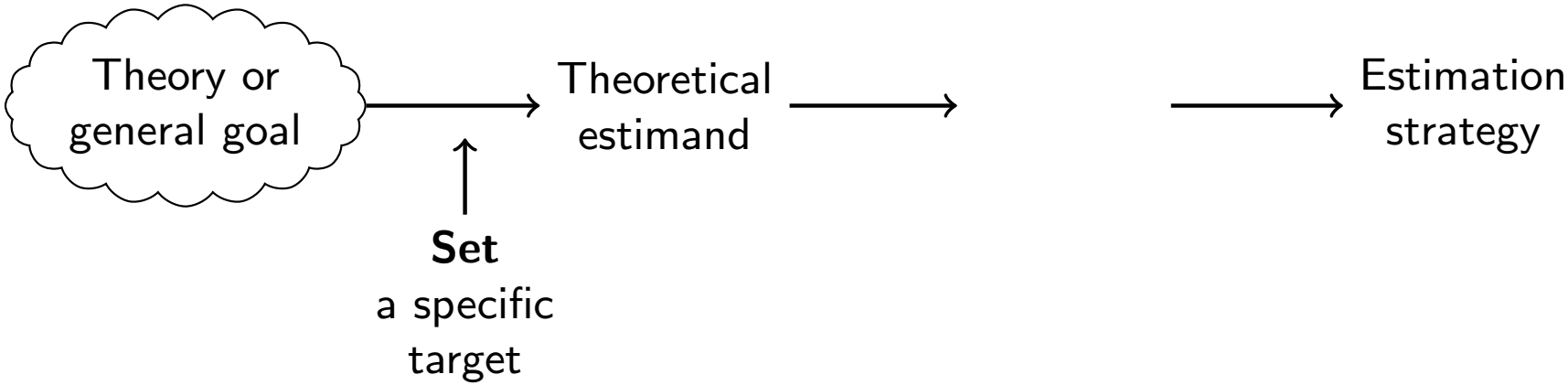

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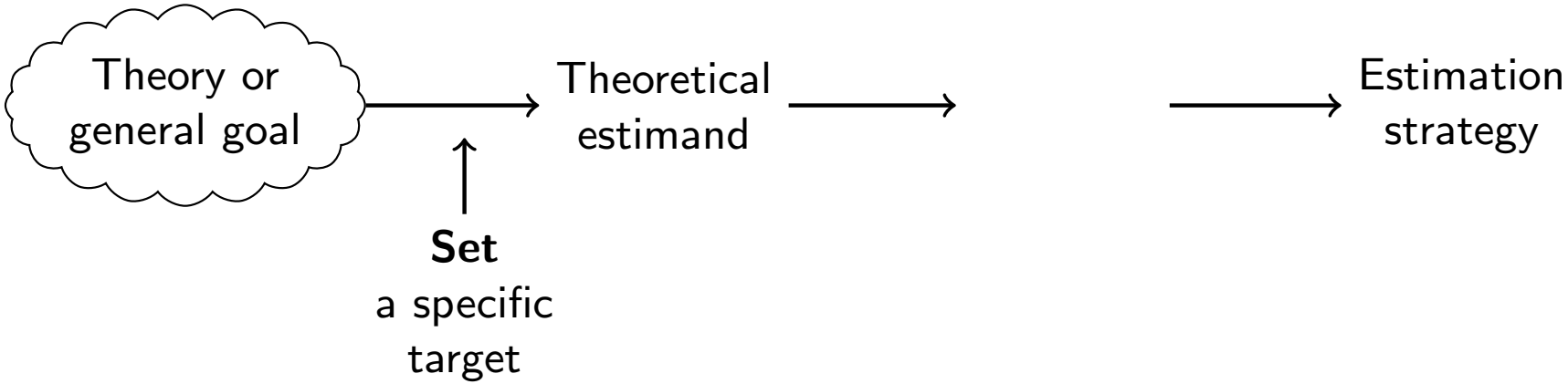

Definition

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

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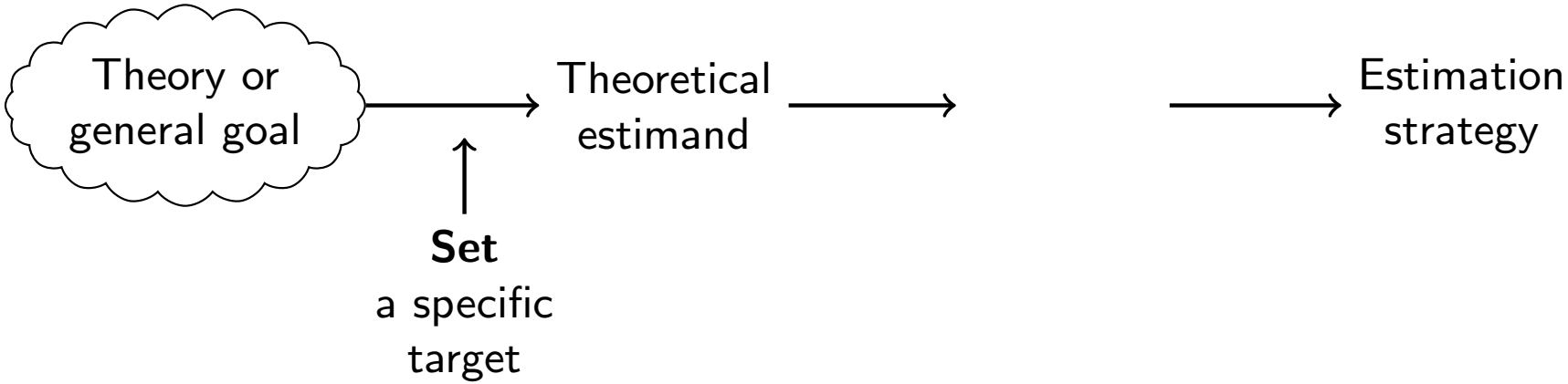

Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \left(\text{Employed}_i\right)$

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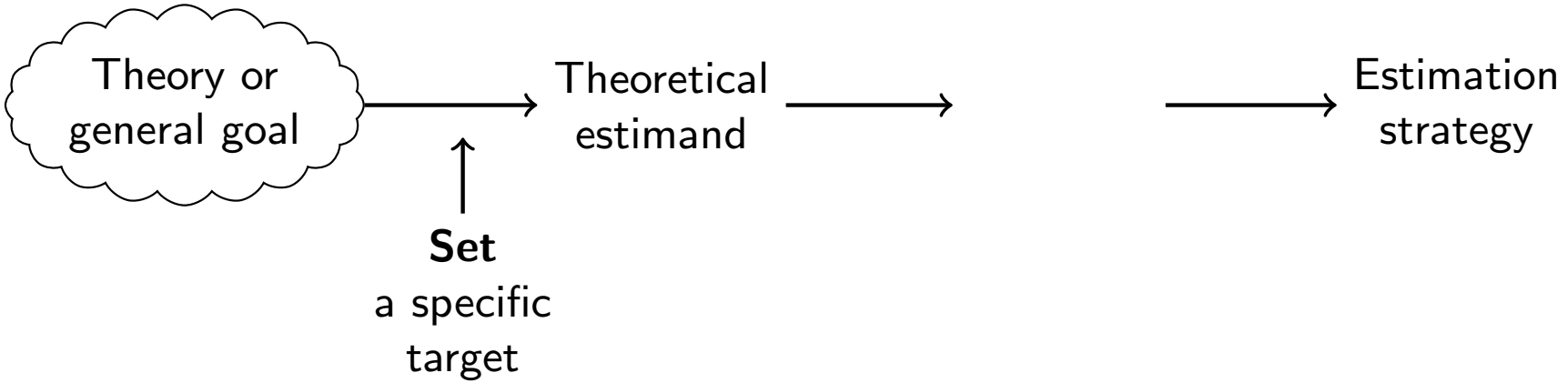

Definition	Example
A **unit-specific quantity** aggregated over a **target population**	$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \Big(\underbrace{\text{Employed}_i(\text{Job training})}_{\text{Employment if received job training}} - \underbrace{\text{Employed}_i(\text{No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

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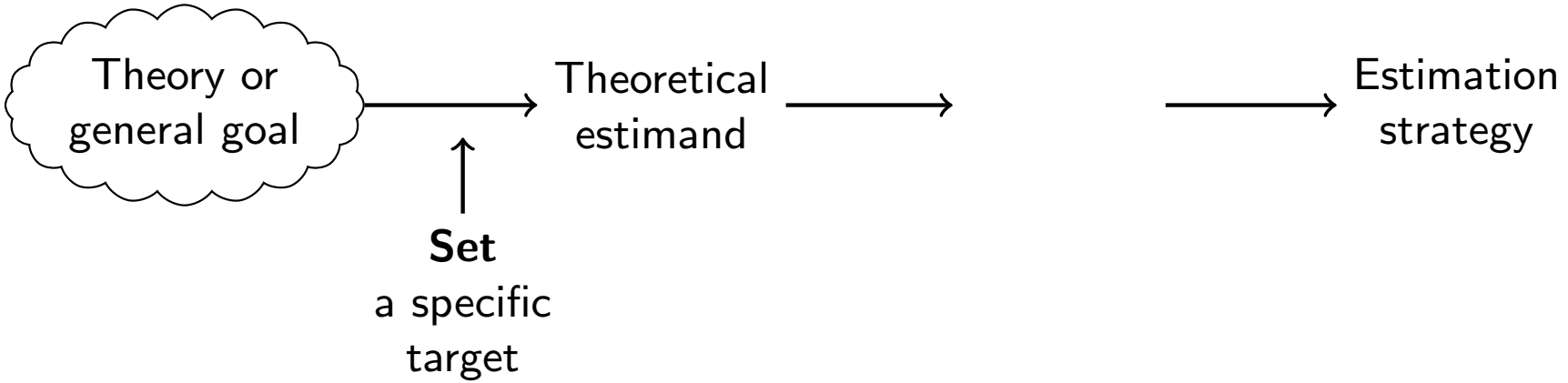

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Lieberson 1987, Abbott 1988, Freedman 1991, Xie 2013, Hernán 2018

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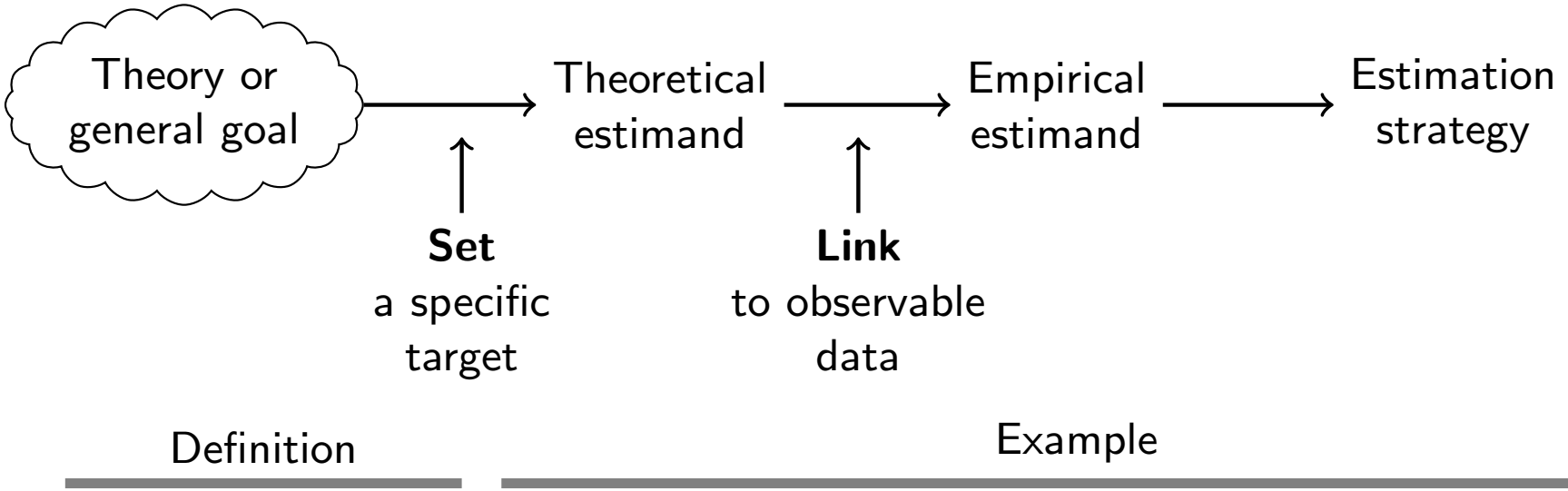

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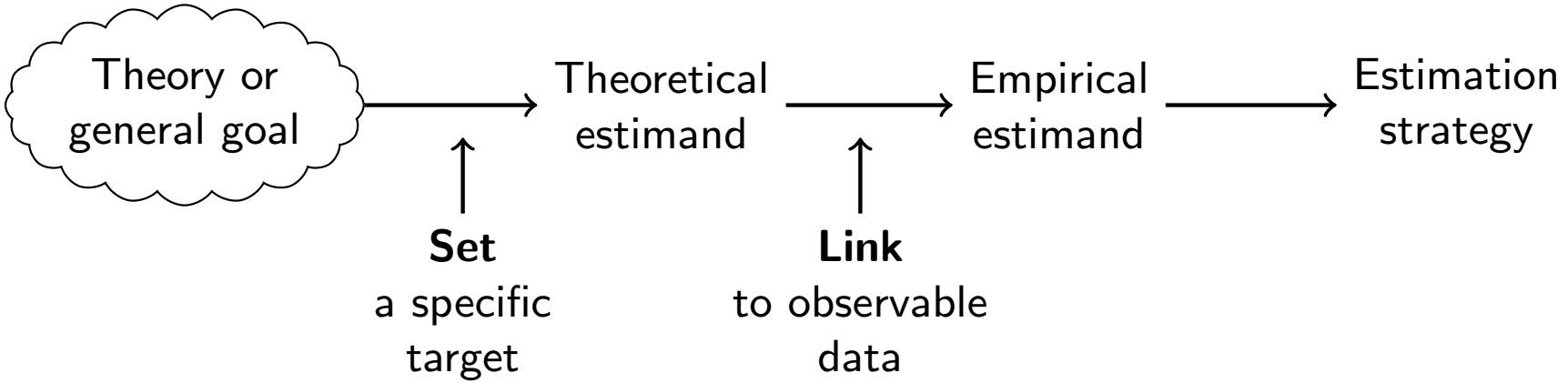

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A quantity involving **observable data**	

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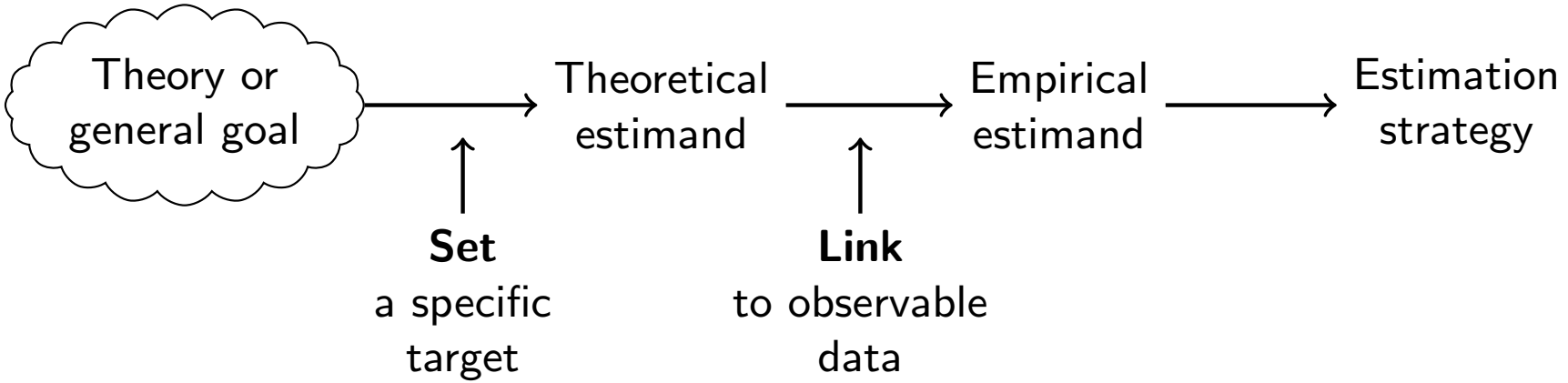
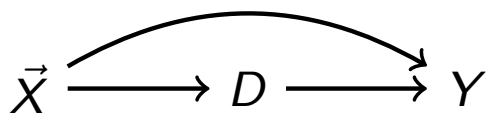


Definition	Example
A quantity involving **observable data**	$\theta = \underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{\text{Sample average}} \left(\underbrace{\mathrm{E}(Y \mid \vec{X} = \vec{x}_i, D = 1)}_{\text{Expected outcome among those treated}} - \underbrace{\mathrm{E}(Y \mid \vec{X} = \vec{x}_i, D = 0)}_{\text{Expected outcome among those untreated}} \right)$



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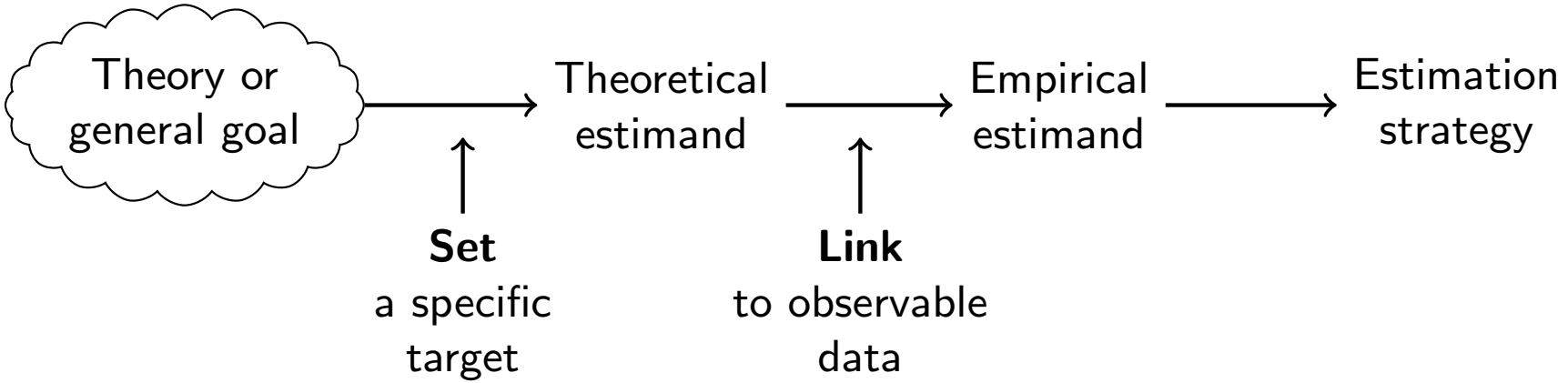

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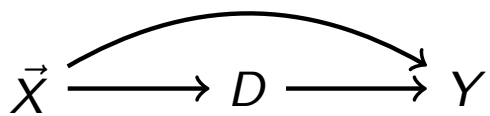

Pearl 2009, Imbens and Rubin 2015,
Morgan and Winship 2015, Elwert and Winship 2014

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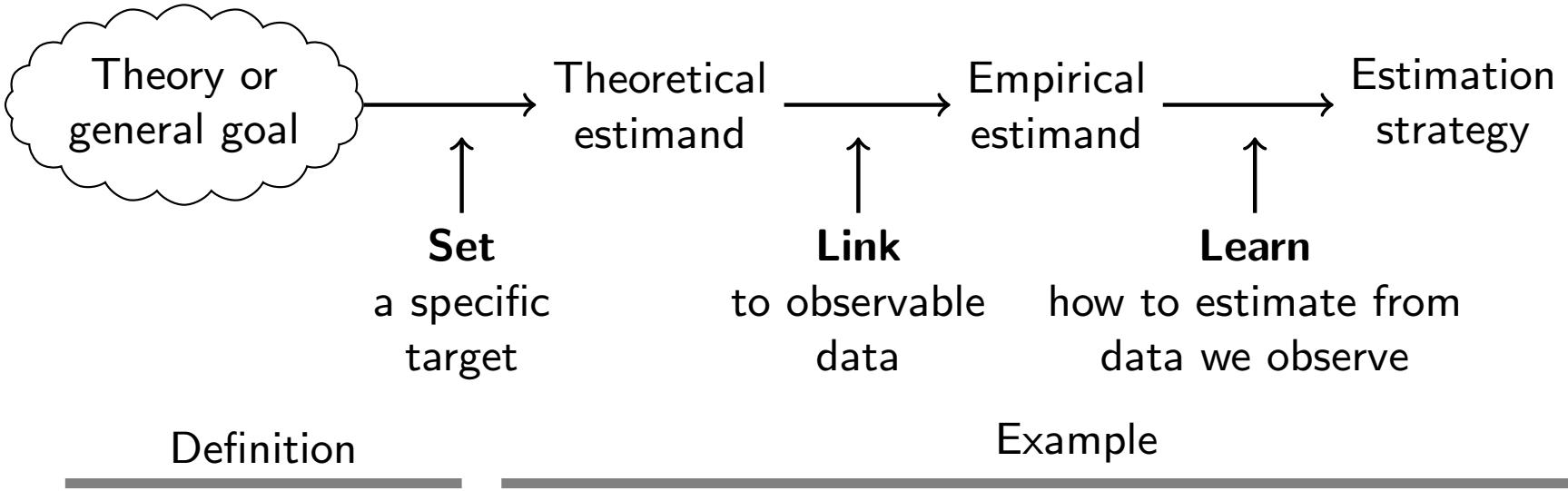

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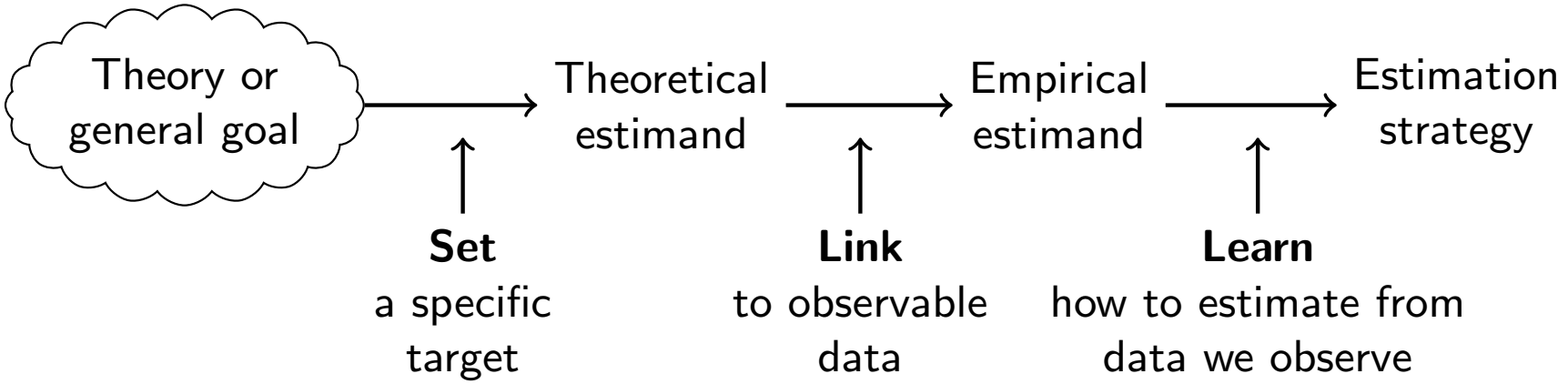
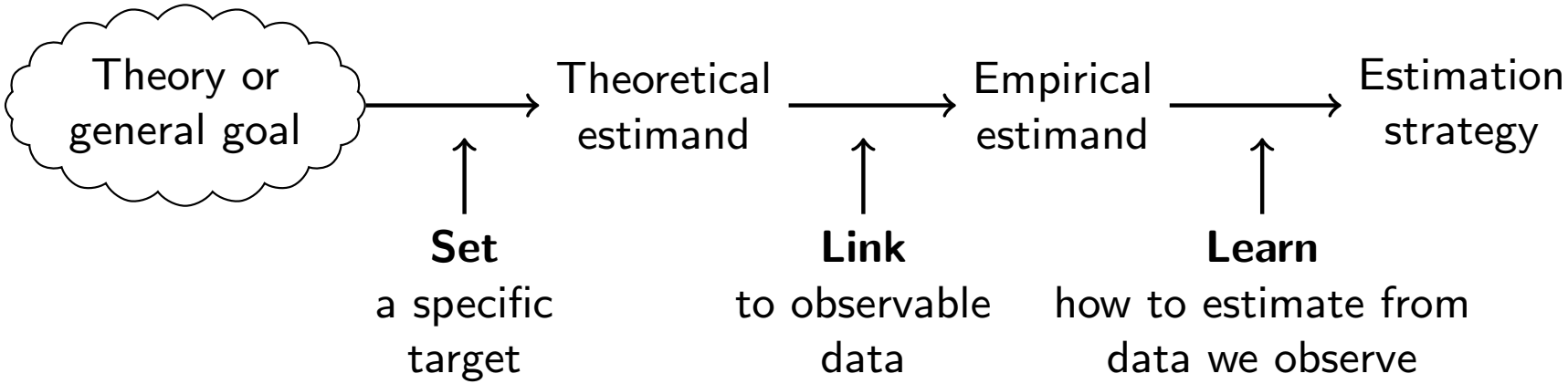


Definition	Example
An algorithm applied to data	

Our solution: A framework centered on **estimands**



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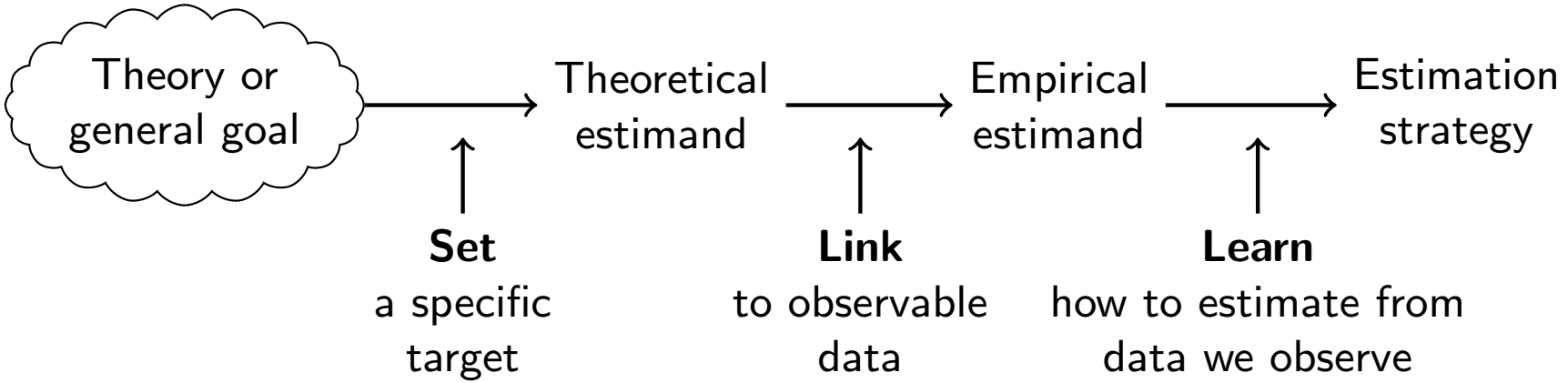

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Young 2009, Watts 2014, Berk et al. 2019, Molina and Garip 2019

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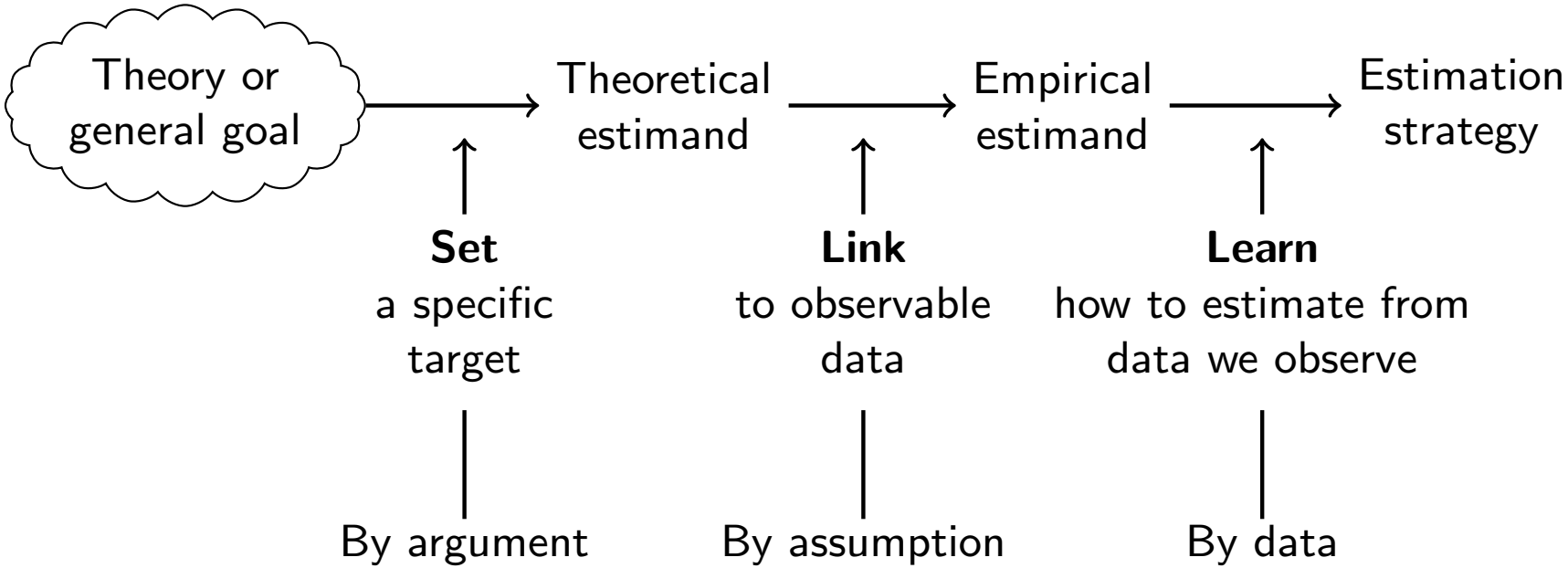
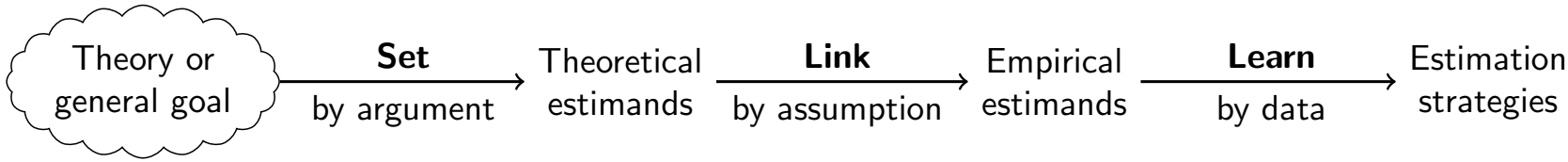
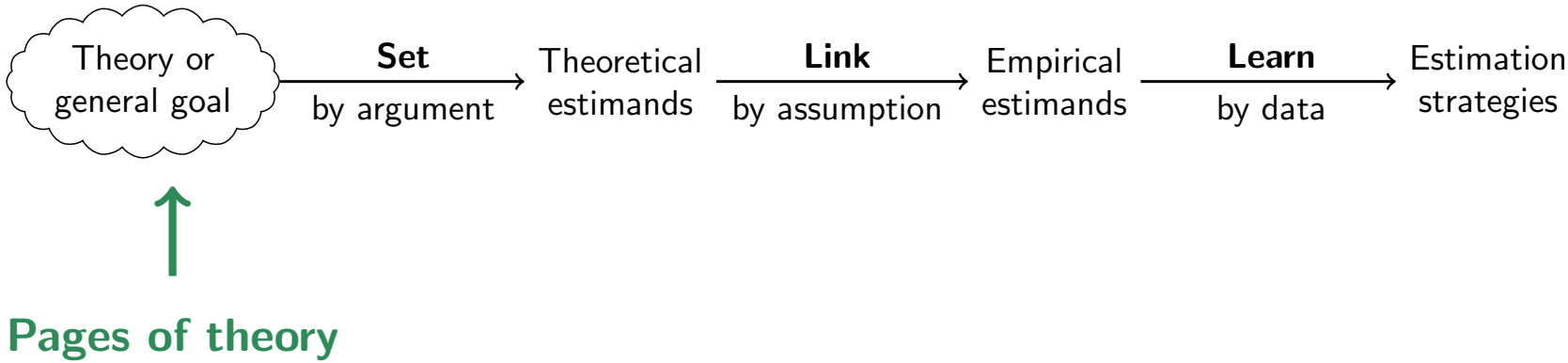



Theory or general goal
Set
by argument
Theoretical estimands
Link
by assumption
Empirical estimands
Learn
by data
Estimation strategies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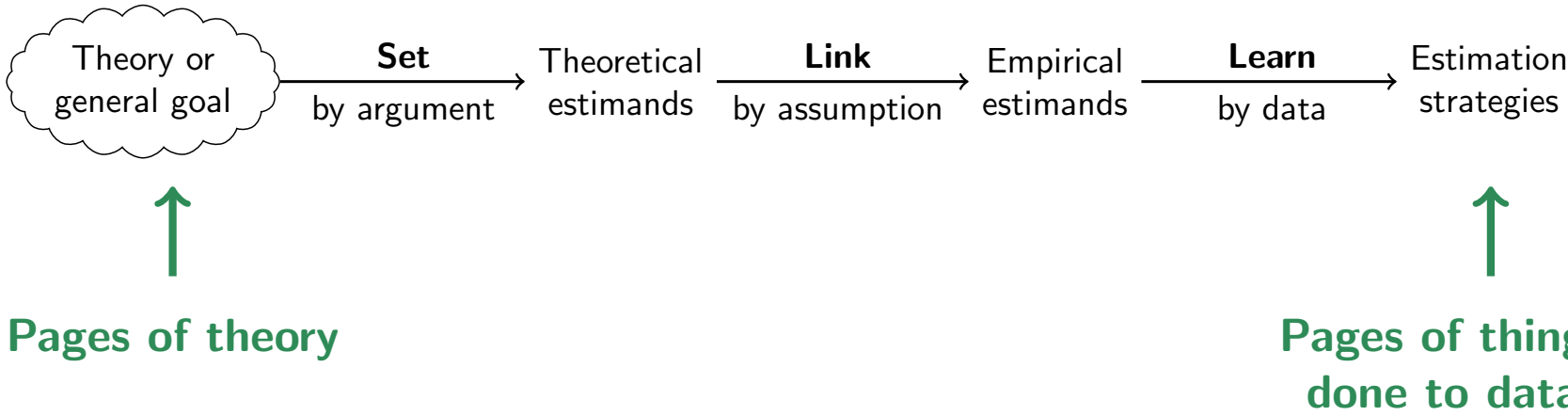
Pages of theory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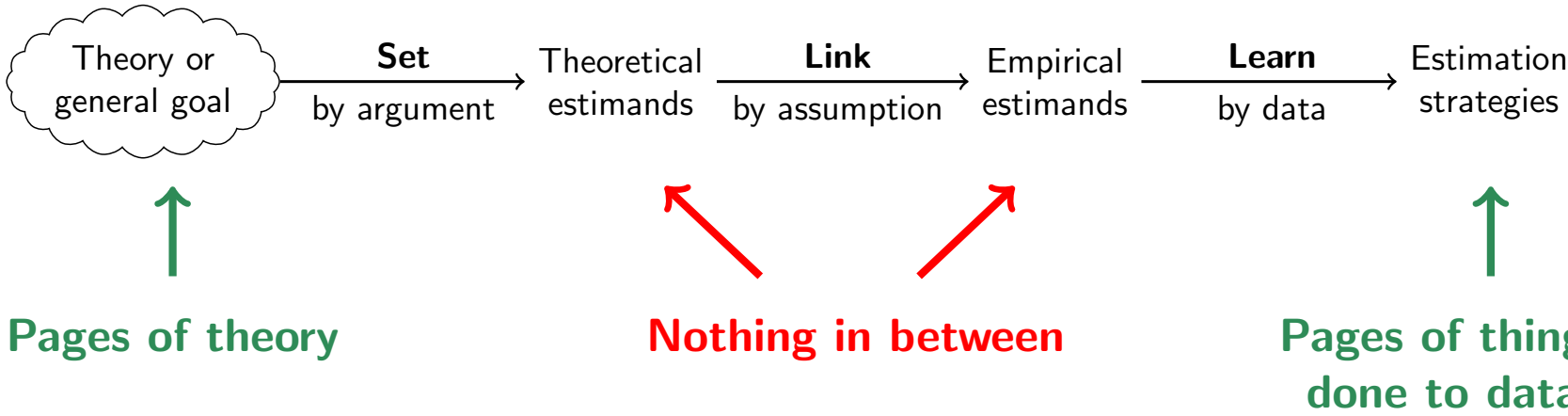
Pages of things done to data



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Systematic Review

All 32 articles in ASR 2018 using quantitative data

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Clarity about **causal claims** (if any)

Systematic Review
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Clarity about the **target population**

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Clarity about **causal claims** (if any)

3 types of articles with distinct issues

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

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

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

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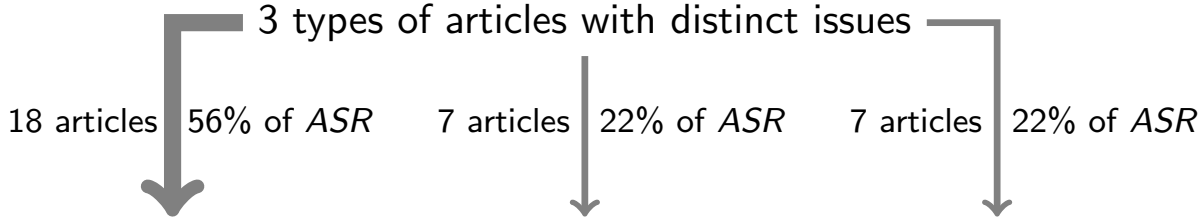

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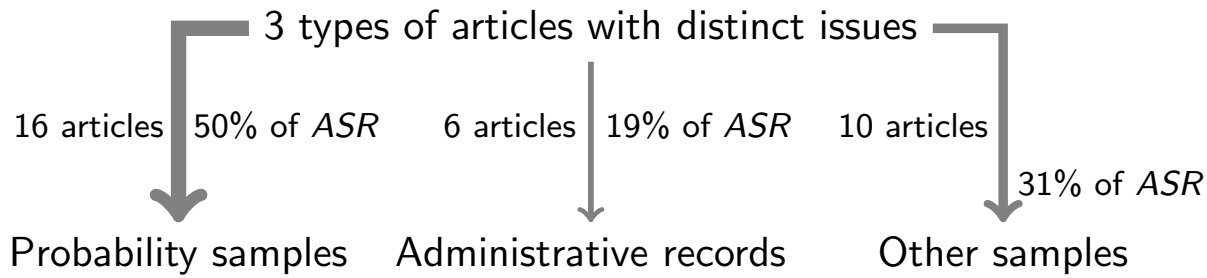

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16 articles	6 articles	10 articles
50% of *ASR*	19% of *ASR*	31% of *ASR*
Probability samples	Administrative records	Other samples
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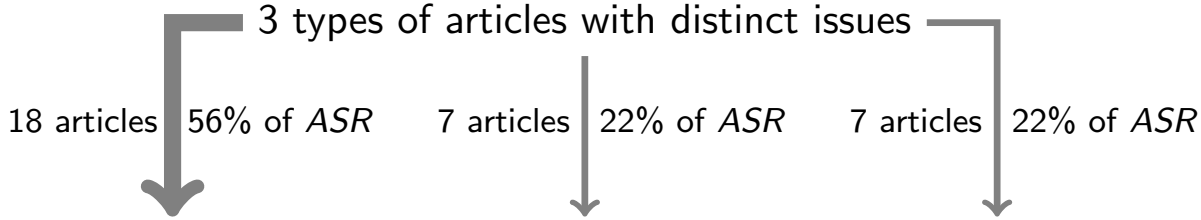

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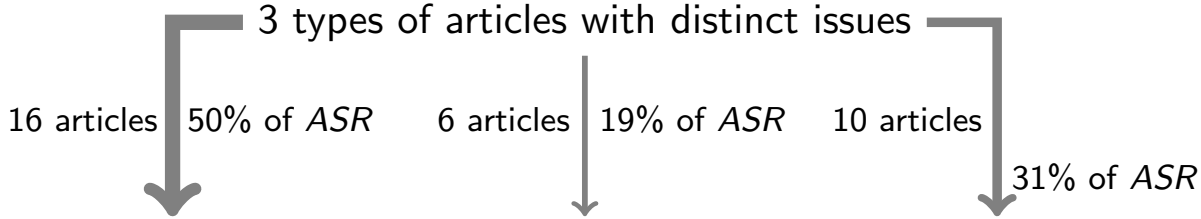

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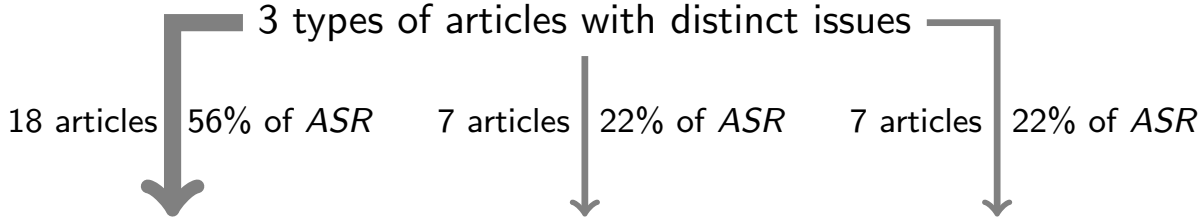

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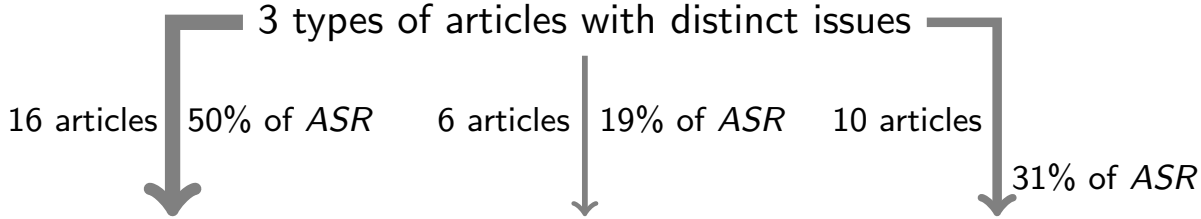

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Confusion about methods

Confusion about conflicting studies

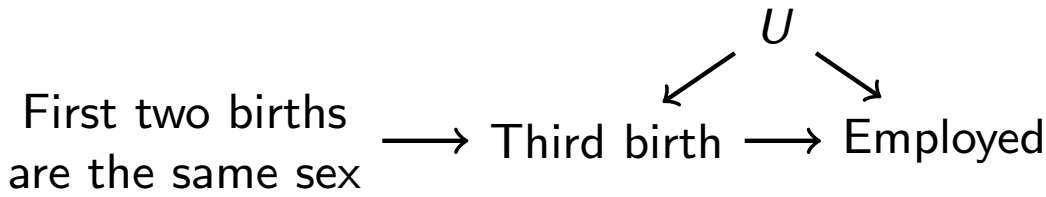
Angrist and Evans 1998

First two births
are the same sex

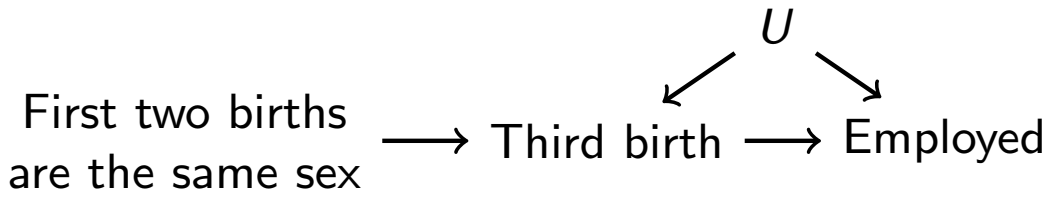
Angrist and Evans 1998

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

Angrist and Evans 1998

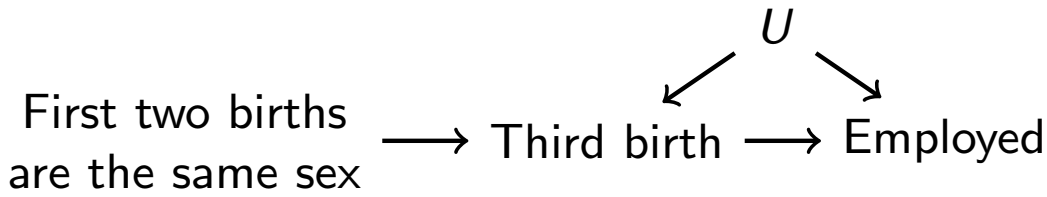


Angrist and Evans 1998



Target population is limited:

Angrist and Evans 1998



Target population is limited:

— At most 53% of mothers have 2+ children

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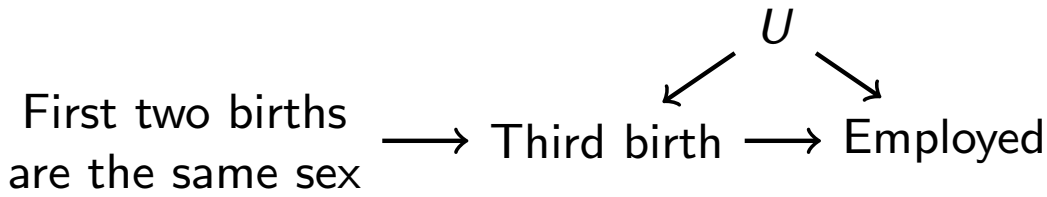

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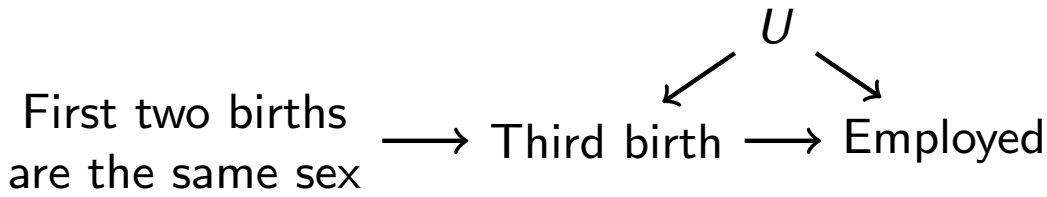
— The complier population is at most 7%

Angrist and Evans 1998



Target population is limited:

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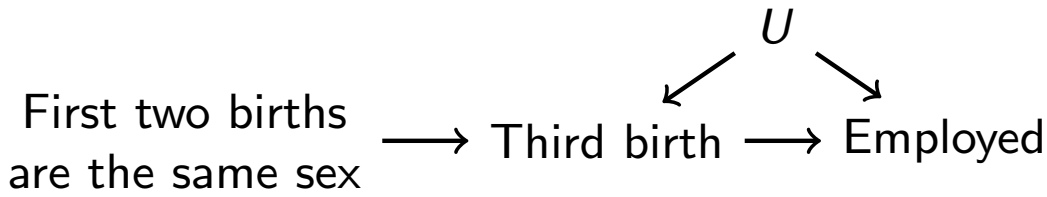
— Target population: at most 53% $\times$ 7% $=$ 4% of mothers

Angrist and Evans 1998



Target population is limited:

— At most 53% of mothers have 2+ children

— The complier population is at most 7%

— Target population: at most 53% $\times$ 7% $=$ 4% of mothers

Causal contrast is limited:

— Having 3 vs. 2 children

Angrist and Evans 1998

Vague statement

Effect of motherhood on employment

Vague statement

Effect of motherhood on employment

Precise statement

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

causal contrast

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

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Not just problems with instruments.

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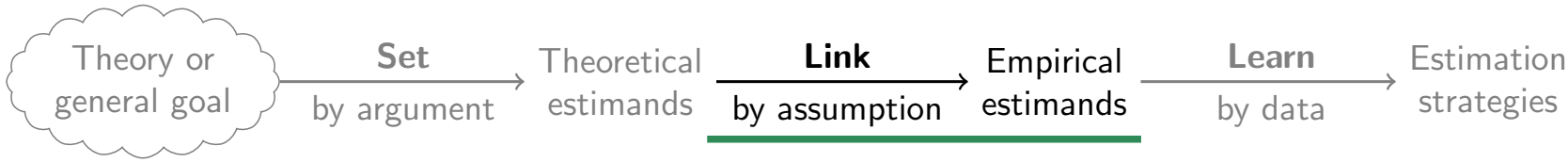
— Causal contrast is vague when the treatment is continuous

— Target population is vague if there are issues of common support


Theory or general goal
Set
by argument
Theoretical estimands
Link
by assumption
Empirical estimands
Learn
by data
Estimation strategies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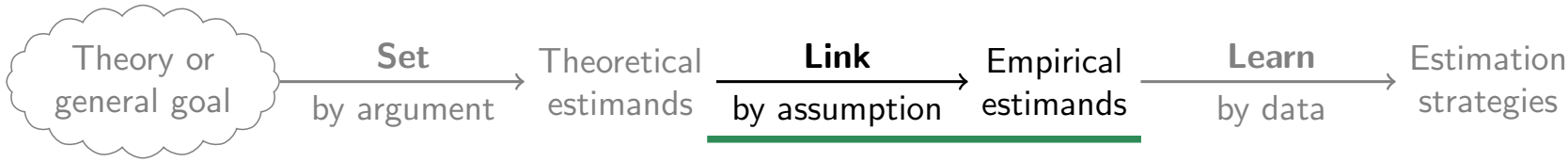
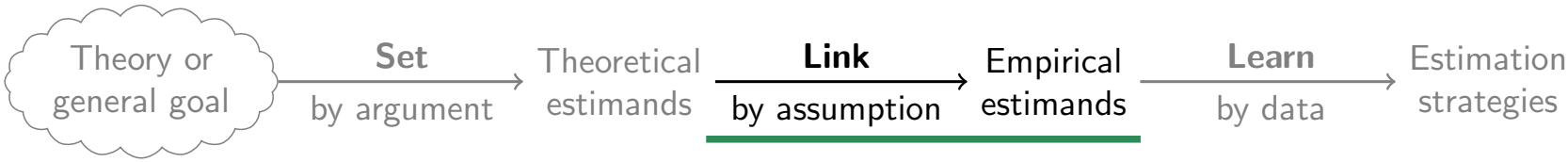
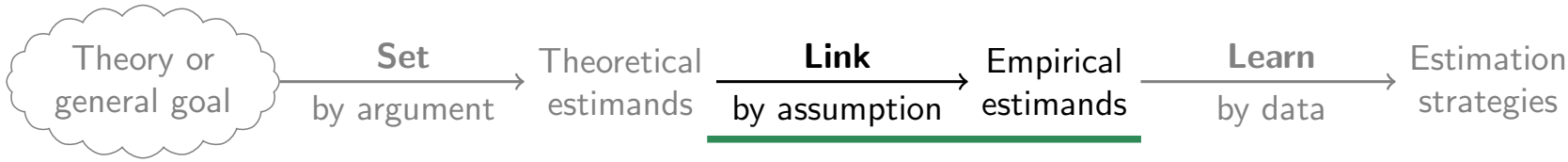


Identification assumptions

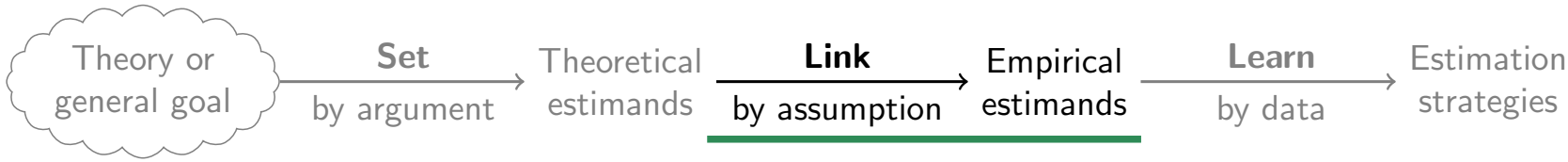


Identification assumptions

are essential even for claims that appear to be **non-causal**



Fryer 2019. See a fuller critique by Knox et al. 2020.



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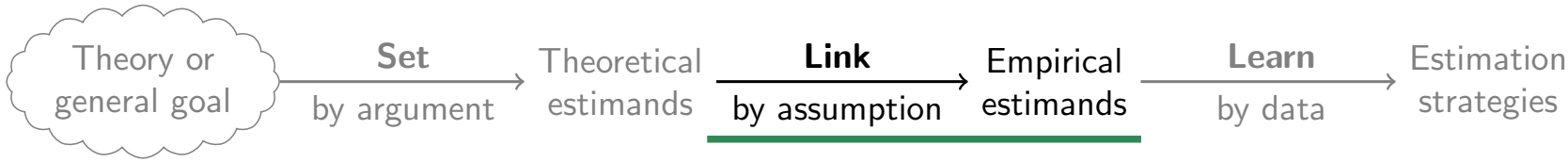

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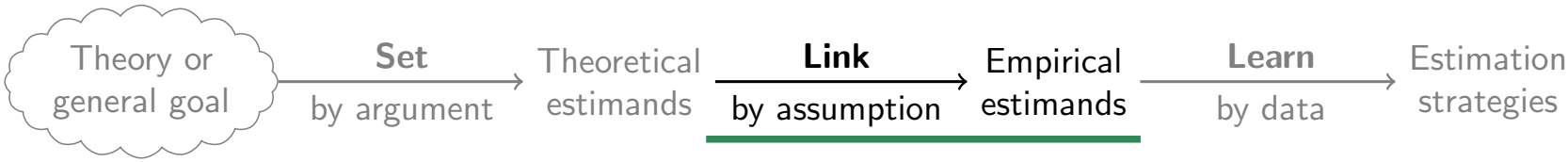

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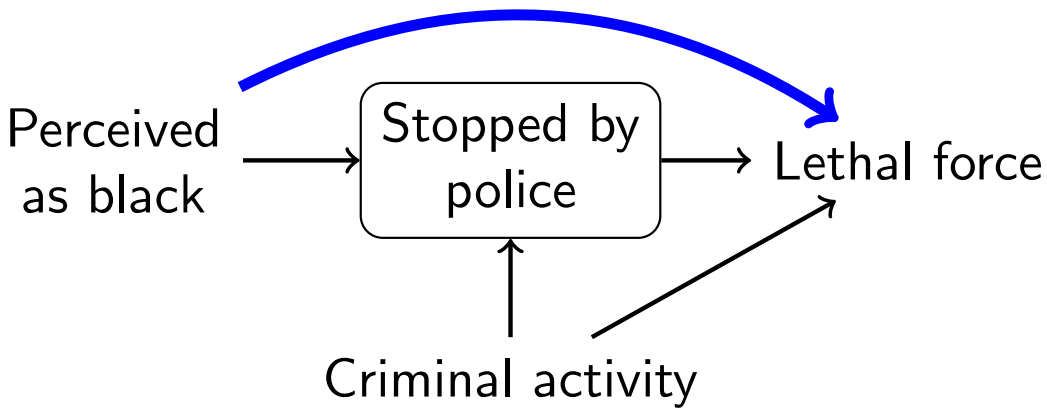

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A **statistical model** enters here (and only here)

Pal and Waldfogel 2017

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^{n} \Big(\hat{\mathrm{E}}(Y \mid \vec{X} = \vec{x}_i, \text{Motherhood} = \text{Mother}) - \hat{\mathrm{E}}(Y \mid \vec{X} = \vec{x}_i, \text{Motherhood} = \text{Non-mother}) \Big)$$

Pal and Waldfogel 2017

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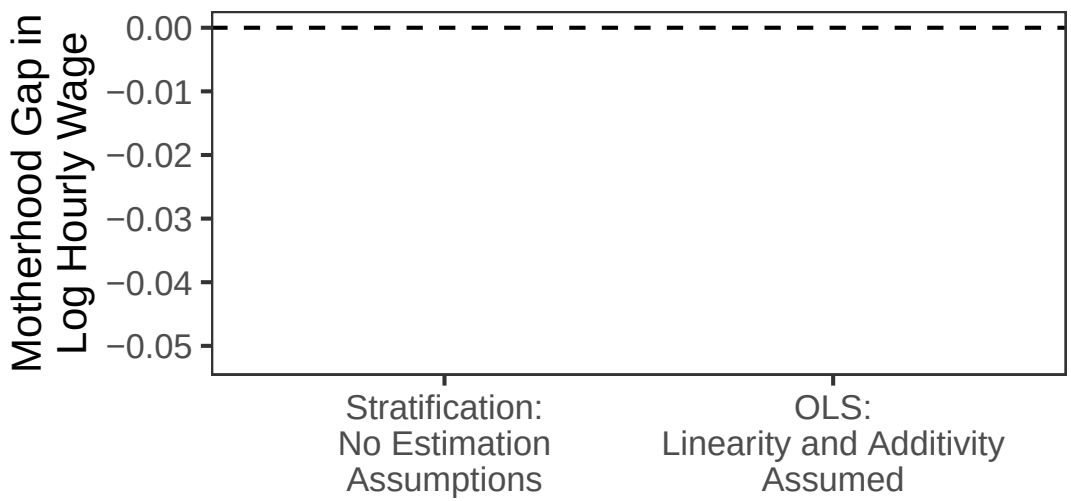

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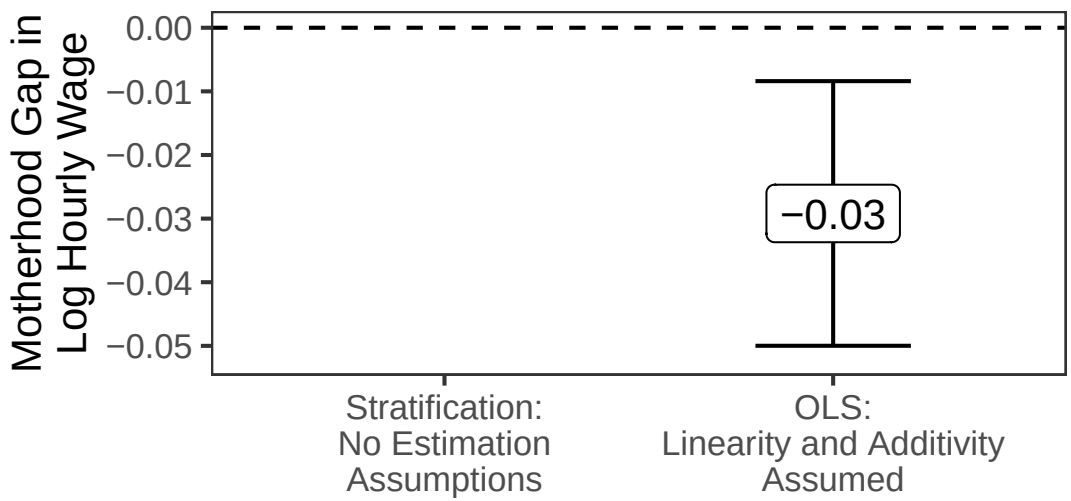

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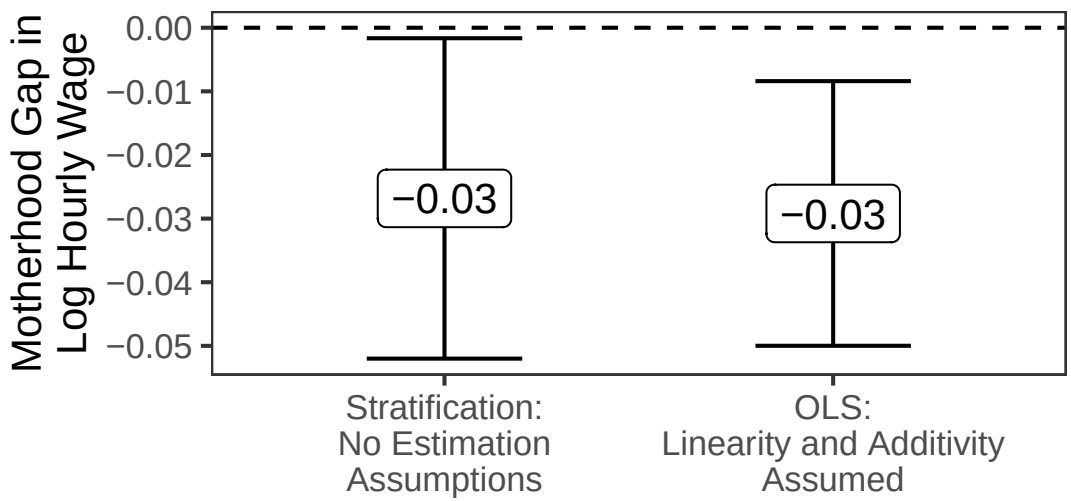

Pal and Waldfogel 2017

Setting the empirical estimand frees us to learn under more **credible** estimation assumptions

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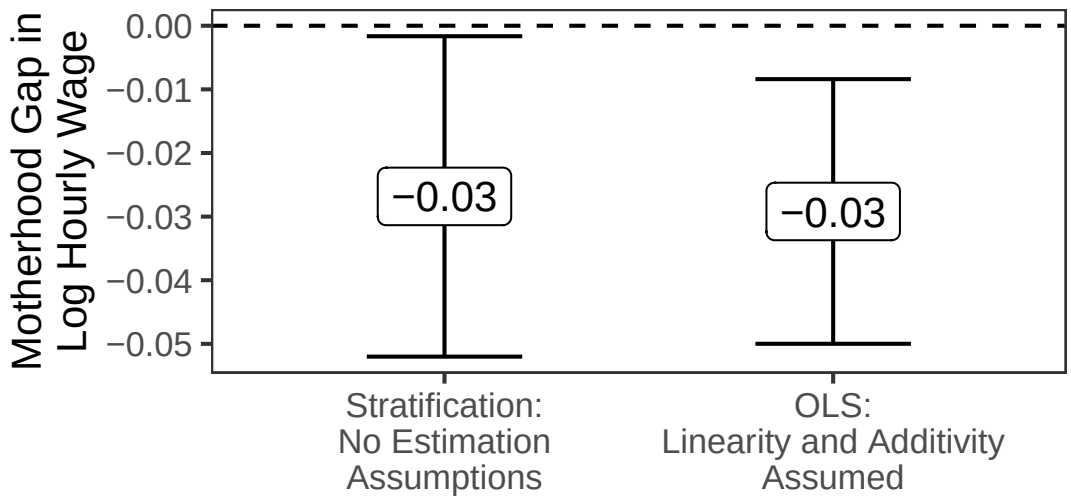

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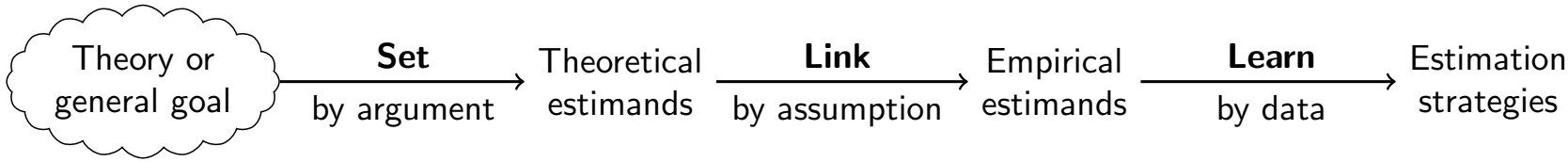
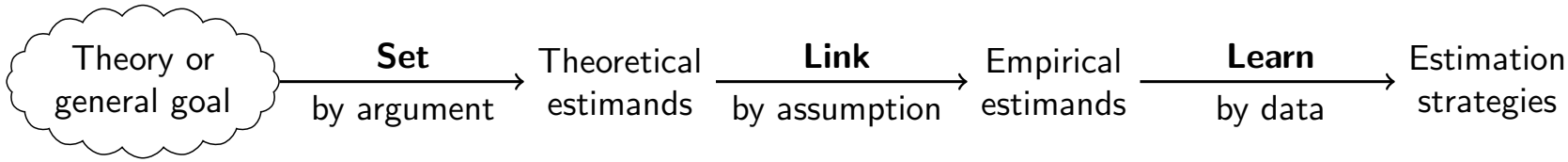


Precise estimands would **clarify confusion** in the literature



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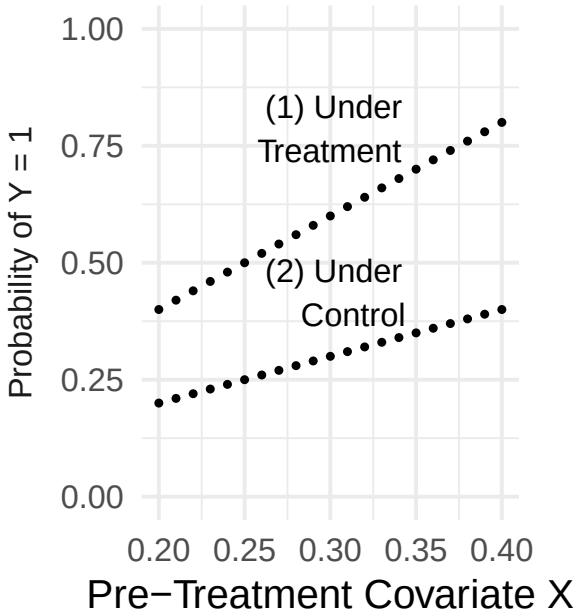

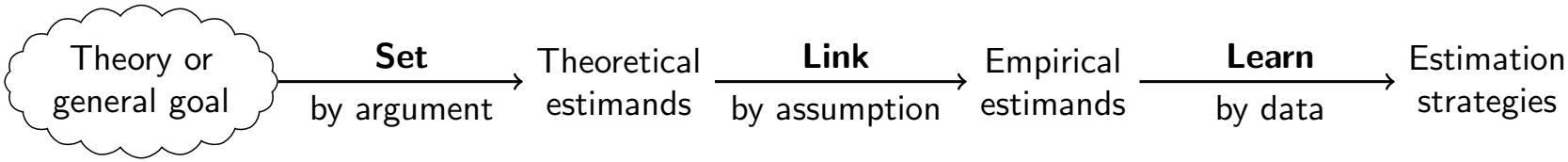

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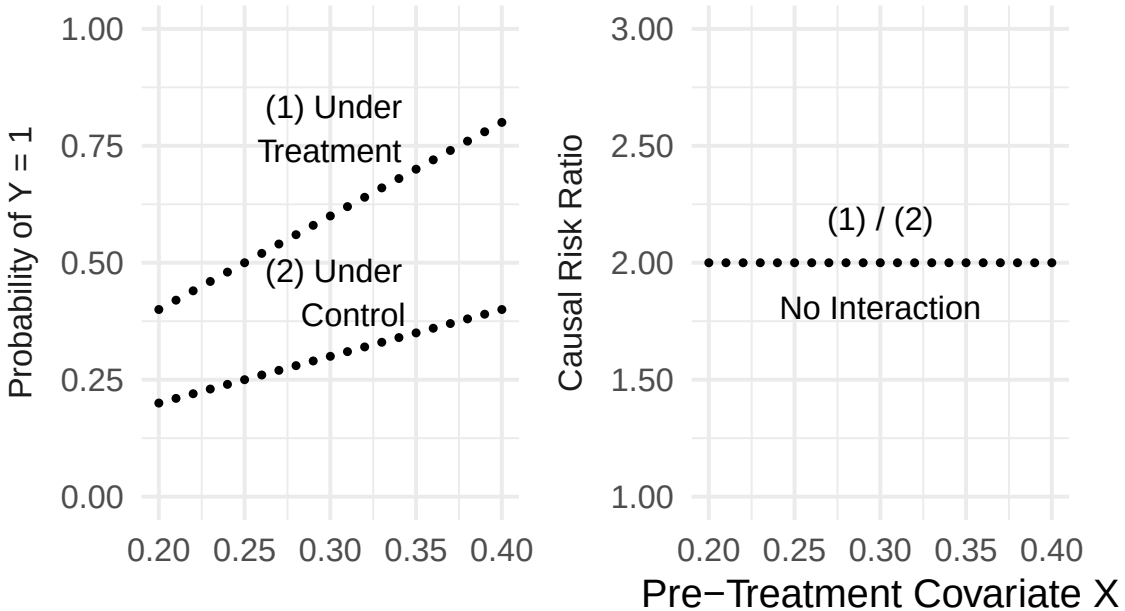

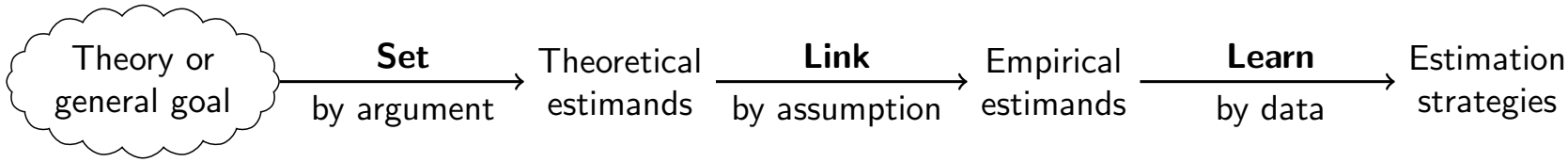

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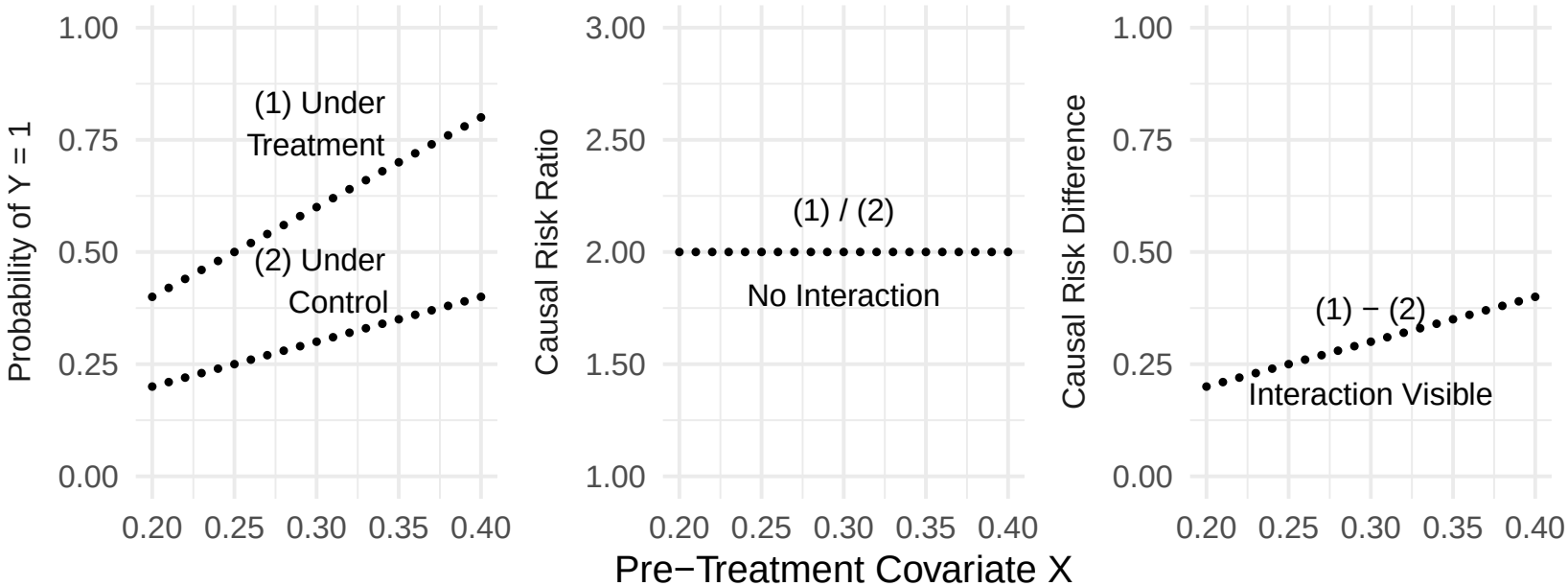

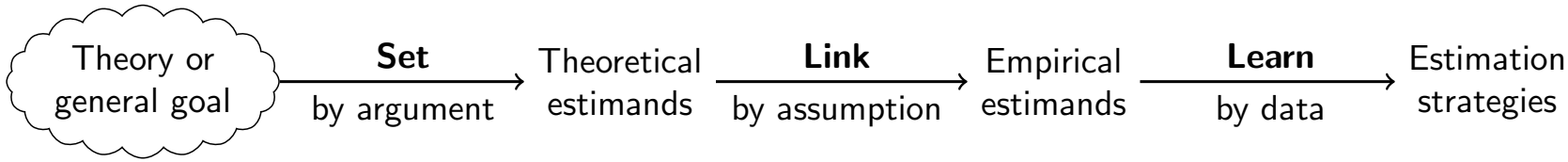

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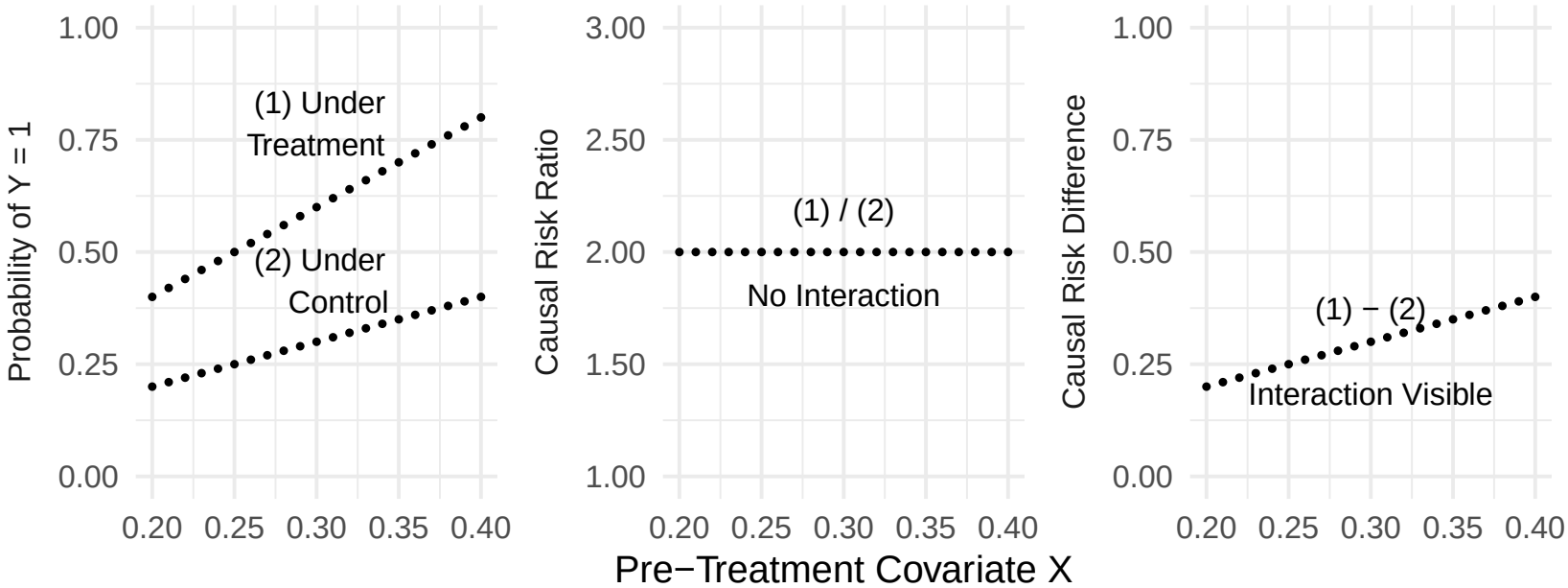
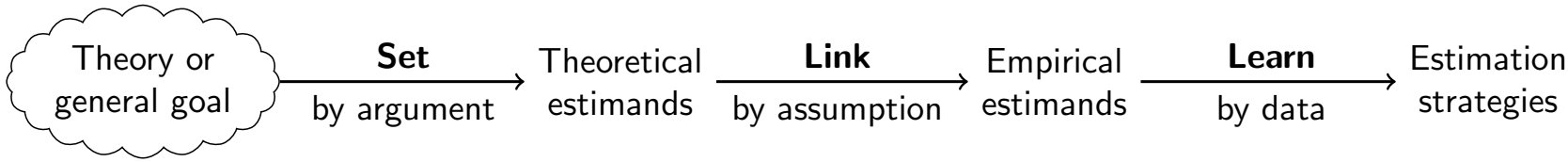


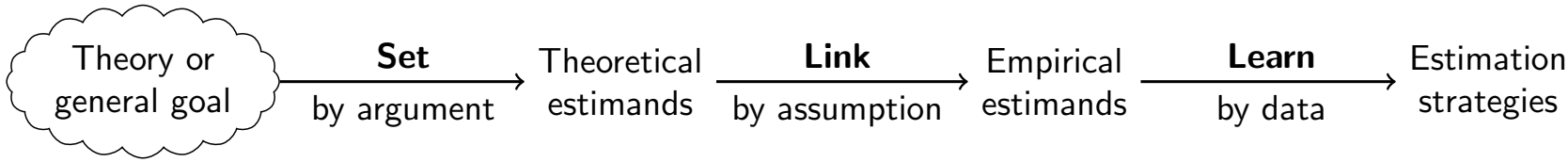
It depends on the **estimand**

Lundberg, Johnson, and Stewart. Setting the Target: Precise Estimands and the Gap Between Theory and Empirics



The **target tautology** is widespread

$\rightarrow$ goals are defined by procedures done to data



The **target tautology** is widespread
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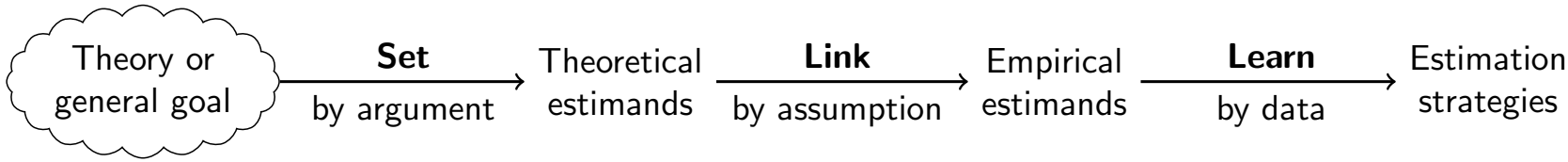
Instead, we should **set the target** nonparametrically
→ could be approximated by many candidate procedures



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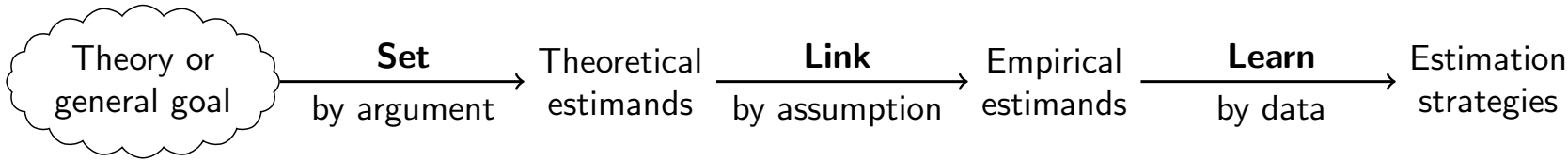
Estimands bring **benefits** to everyone.



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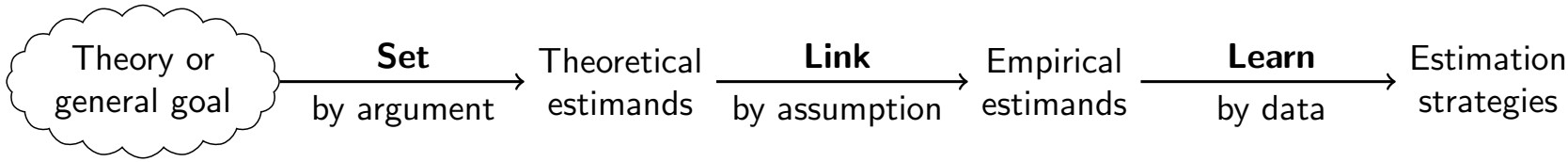

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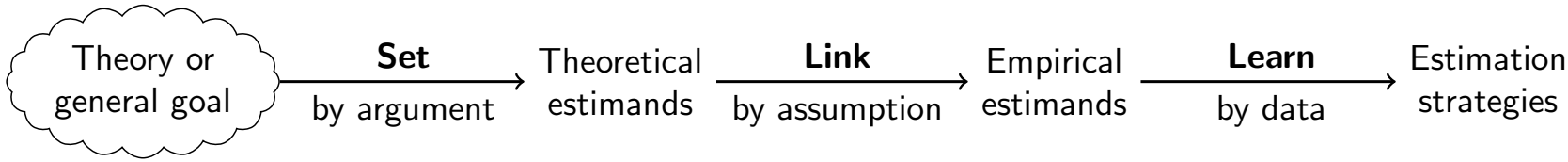

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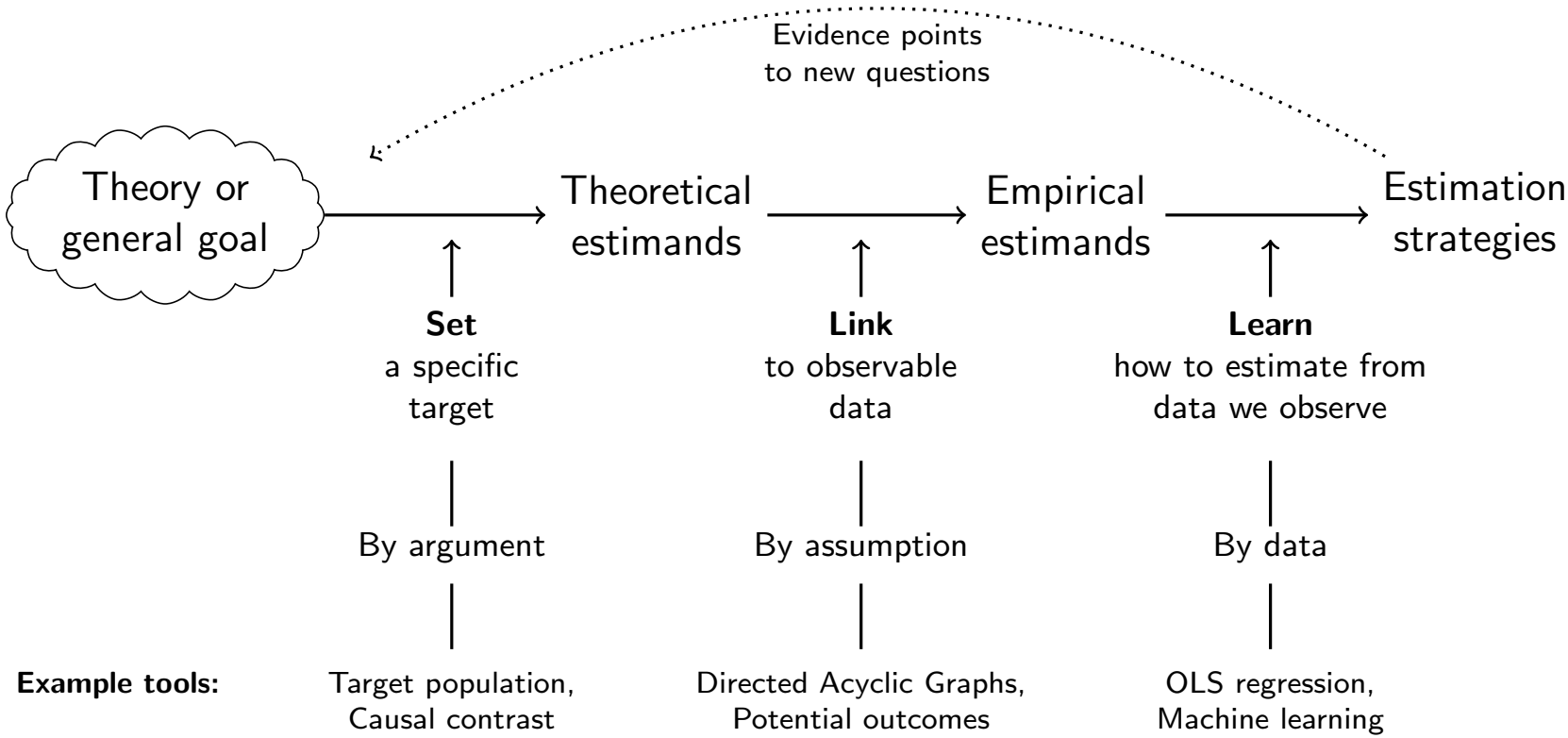
- Estimands help the **community** to clarify the contribution of each paper



Paper on SocArxiv.
Replication code on GitHub.
Slides on GitHub.