

Non-existent outcomes in research on inequality: A causal approach

Ian Lundberg

UCLA Sociology and
California Center for
Population Research

Soonhong Cho

UCLA Political Science and
California Center for
Population Research

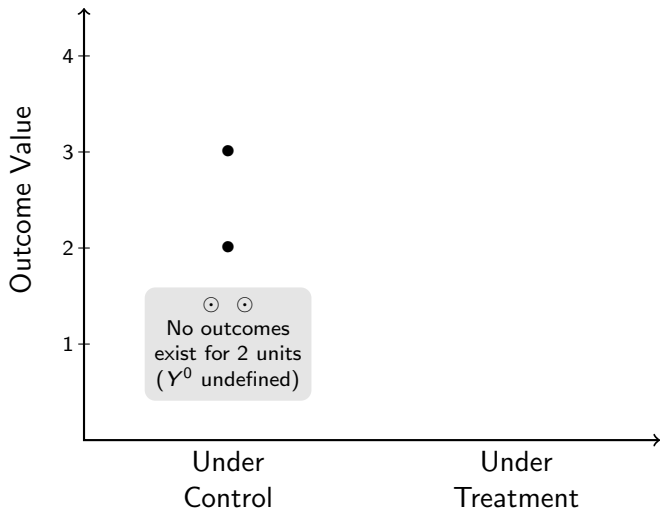
28 June 2025

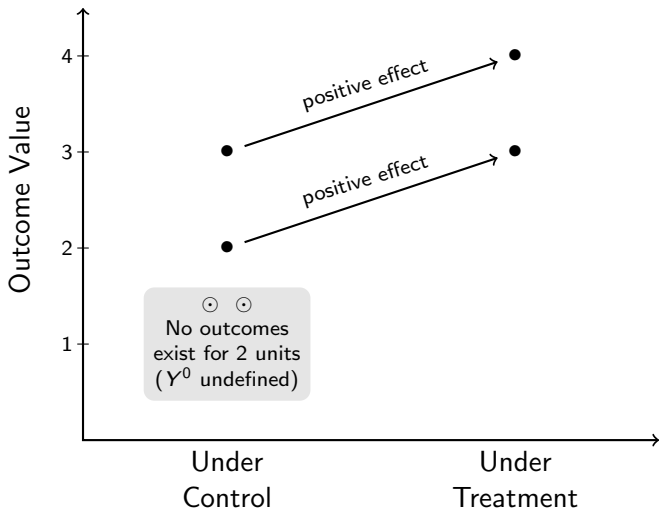
University of Tokyo

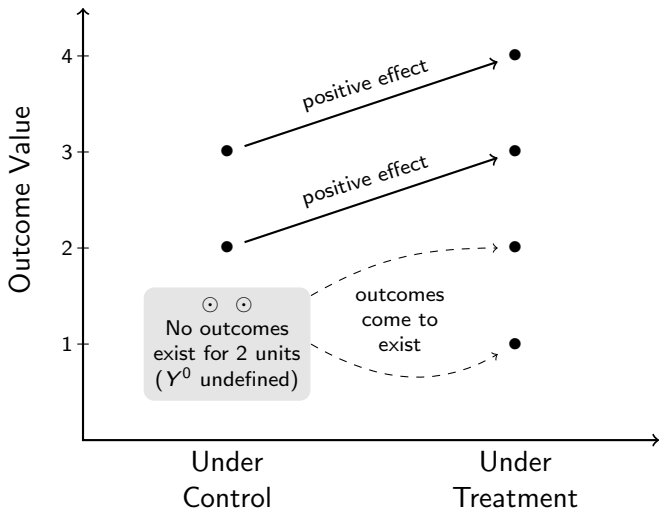
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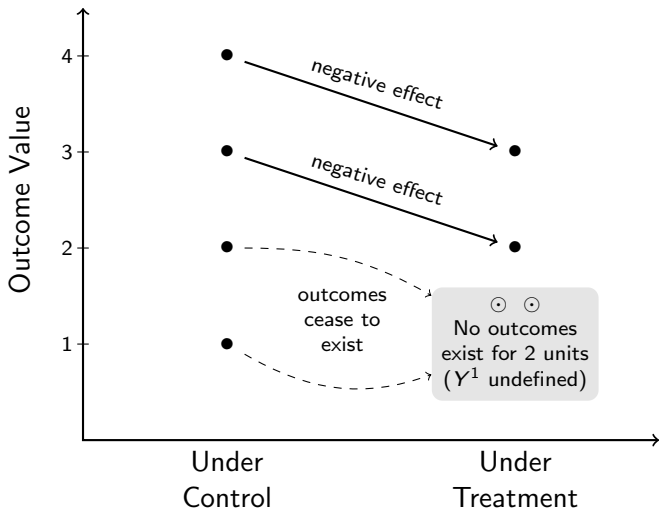
Some outcomes exist only for some people

- ▶ only employed people have an hourly wage
- ▶ only married people can report marital satisfaction
- ▶ only people with children have descendants









Our goals in this paper

When researchers drop missing outcomes,

- ▶ inequality can be obscured
- ▶ we may miss causal effects

We provide methods to study both:

- ▶ effects on outcome existence (employment)
- ▶ effects on outcome values (wage)

One concrete setting

Parenthood reduces hourly wages for women

(Budig & England 2001; Gough & Noonan 2013)

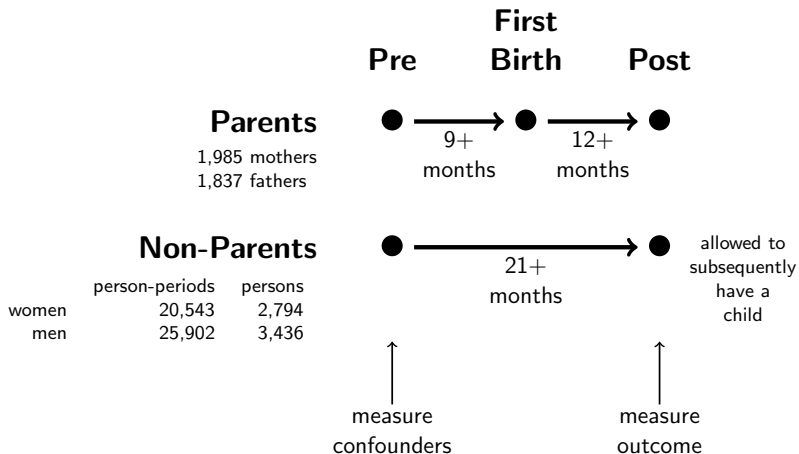
and increases wages for men

(Killewald 2013; Yu & Hara 2021)

The motherhood wage penalty may be disappearing over time

(Pal & Waldfogel 2016; Buchmann & McDaniel 2016; but see Jee et al. 2019)

Data: NLSY97



$$\begin{aligned}\log(\text{Wage}) = & \beta_0 + \beta_1(\text{Mother}) \\ & + \beta_2(\text{Age}) \\ & + \beta_3(\text{Married}) \\ & + \beta_4(\text{Education}) \\ & + \beta_5(\text{Work Experience}) \\ & + \beta_6(\text{Full-Time}) \\ & + \beta_7(\text{Tenure in Job}) \\ & + \epsilon\end{aligned}$$

Maya

Maya

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
wage		—		=	

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	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
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	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
wage		—		=	

Maya

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	0
wage		—		=	

Maya

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	0
wage	\$30	—		=	

Maya

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	0
wage	\$30	—	\$40	=	

Maya

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	0
wage	\$30	—	\$40	=	—\$10

Mia

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
wage		—		=	

Mia

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
wage		—		=	

Mia

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	
wage		—		=	

Mia

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	—1
wage		—		=	

Mia

	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	—1
wage	??	—		=	

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	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	—1
wage	??	—	\$20	=	

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	<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
employment		—		=	−1
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Principal Stratification

Frangakis & Rubin 2002; Zhang & Rubin 2003

For an intro, see Miratrix et al. 2018

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	—		=	0
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Nancy

<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
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\$30	—	\$40	=	-\$10

Mia

<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
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Nia

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	—		=	-1
??	—	\$20	=	??

Maya is a Mother

<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
	—		=	0
\$30	—	\$40	=	-\$10

Nancy is a Non-Mother

<u>if a mother</u>	—	<u>if not</u>	=	<u>effect</u>
	—		=	0
\$30	—	\$40	=	-\$10

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DROPPED

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Average Observed

\$30

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1) Average effect of motherhood on employment

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	—		=	-1
??	—	\$20	=	??

- 1) Average effect of motherhood on employment
- 2) Wage effect among those employed regardless

Goal 1: Effect on outcome existence

Causal Estimand

Define potential outcomes:

S^1 = whether employed as a parent

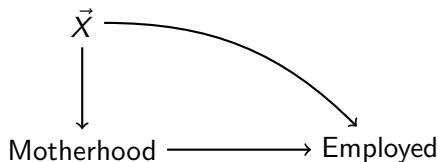
S^0 = whether employed as a non-parent

Causal estimand

$$E(S^1 - S^0 \mid A = 1)$$

Goal 1: Effect on outcome existence

Causal Assumptions



Where $\vec{X}$ includes age, education, marital status, full-time employment, job tenure, work experience, and wage and employment each lagged by one year.

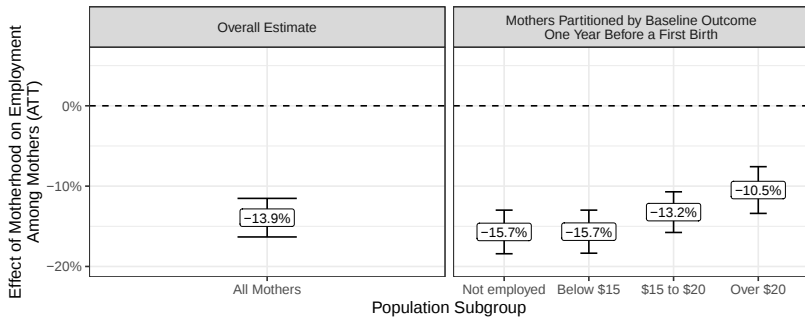
Goal 1: Effect on outcome existence

Estimation Strategy

- ▶ Regress Y on treatment and confounders
- ▶ Predict for all mothers average

$$\frac{1}{n_{\text{Mothers}}} \sum \left(\hat{Y}_i^1 - \hat{Y}_i^0 \right)$$

Results for **mothers**



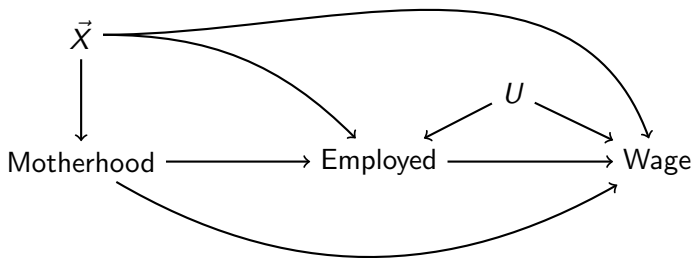
Goal 2: Effect on outcome value

Causal Estimand

$$\tau = E\left(\underbrace{Y^1 - Y^0}_{\text{Effect of Treatment on Outcome Value}} \mid \underbrace{A = 1}_{\text{Among the Treated}}, \underbrace{S^1 = S^0 = 1}_{\text{Whose Outcome Exists Regardless of Treatment}}\right) \quad (1)$$

Effect of motherhood on wage
among mothers who would be employed
as a parent or as a non-parent

Causal assumption: Exchangeability



Causal assumption: Monotonicity

$$S_i^1 \leq S_i^0 \quad \text{for all } i \quad (\text{negative monotonicity}) \quad (2)$$

A woman who would be employed as a non-mother ($S_i^0 = 1$)
would also be employed as a mother ($S_i^1 = 1$)

Causal assumption: Mean dominance

$$\begin{aligned} E(Y^0 \mid \vec{X} = \vec{x}, S^0 = S^1 = 1) &\geq \\ E(Y^0 \mid \vec{X} = \vec{x}, S^0 = 1, S^1 = 0) &\quad \forall \vec{x} \end{aligned}$$

Women employed regardless of motherhood
would have higher mean wages as non-mothers
than women employed only if they were non-mothers

Identification: Making use of the assumptions

Recall that our goal is:

$$\left(\begin{array}{c} \text{mean factual} \\ \text{wage} \end{array} \right) - \left(\begin{array}{c} \text{mean counterfactual wage} \\ \text{as non-mothers} \end{array} \right)$$

among mothers employed regardless of motherhood.

Identification: Mean factual wage as mothers

We observe mothers with a wage distribution



Identification: Mean factual wage as mothers

We observe mothers with a wage distribution



By assumption (monotonicity),
all would also be employed as non-mothers

Identification: Mean factual wage as mothers

We observe mothers with a wage distribution



By assumption (monotonicity),
all would also be employed as non-mothers

Estimate $E(Y^1 \mid A = 1, S^0 = S^1 = 1, \vec{X})$ by the mean.

Identification: Counterfactual wage as non-mothers

Identification: Counterfactual wage as non-mothers

We observe wages
among non-mothers

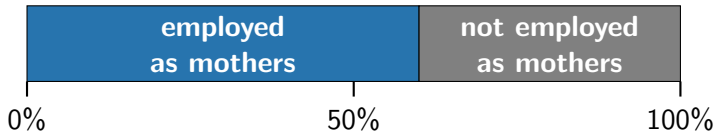


Identification: Counterfactual wage as non-mothers

We observe wages
among non-mothers



But some of them would not be employed as mothers

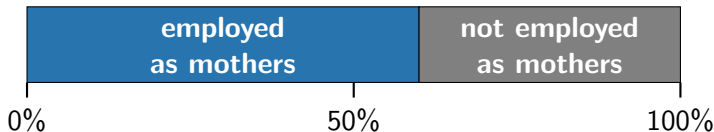


Identification: Counterfactual wage as non-mothers

We observe wages
among non-mothers



But some of them would not be employed as mothers



Two extreme possibilities:



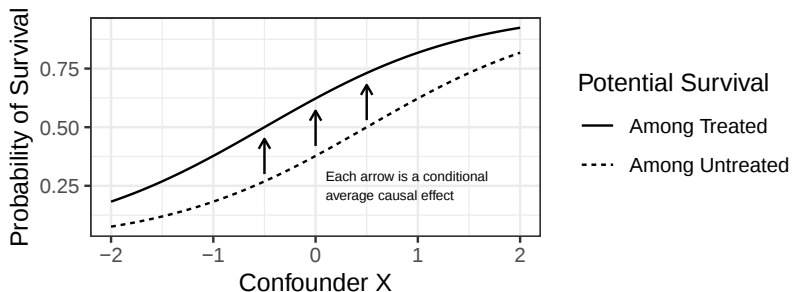
Lower Bound:
Mean of Blue Region



Upper Bound:
Mean of Blue Region

Estimation by regression and simulation

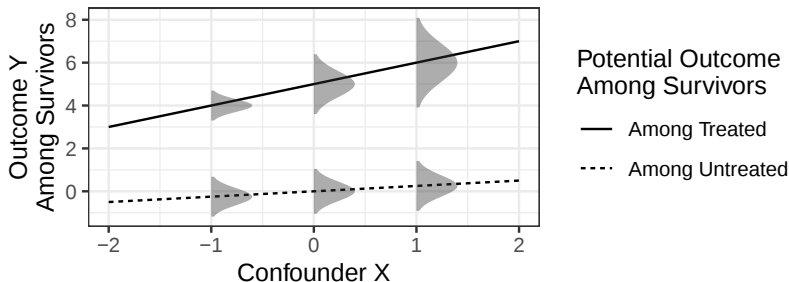
Example:
Logistic regression for survival



Estimation by regression and simulation

Example:

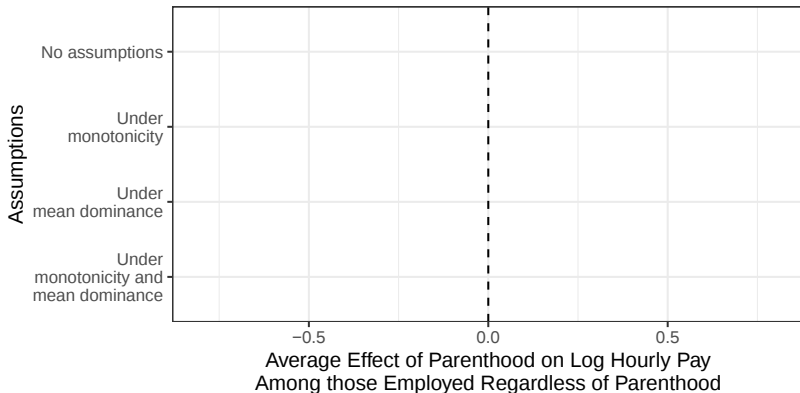
Heteroskedastic regression for conditionally normal outcomes among survivors



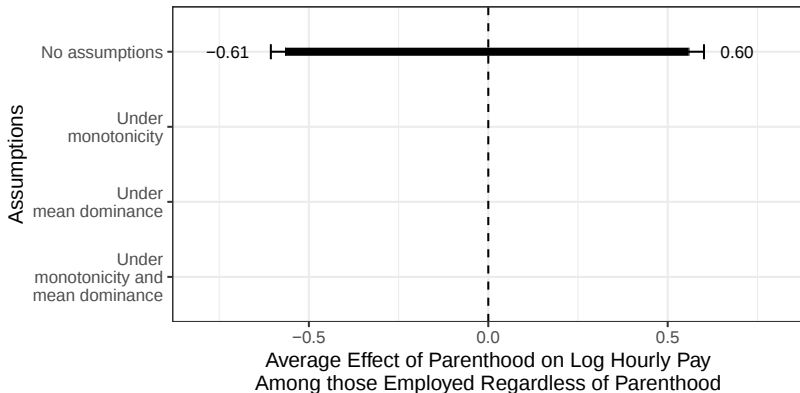
Review of our strategy

1. Define the causal estimands
2. Make causal assumptions (e.g., DAG + monotonicity)
3. Model Y among those with outcomes
4. Simulate a distribution for counterfactual estimation
5. Create bounds by considering extremes
 - ▶ Target subgroup are the **highest** paid
 - ▶ Target subgroup are the **lowest** paid

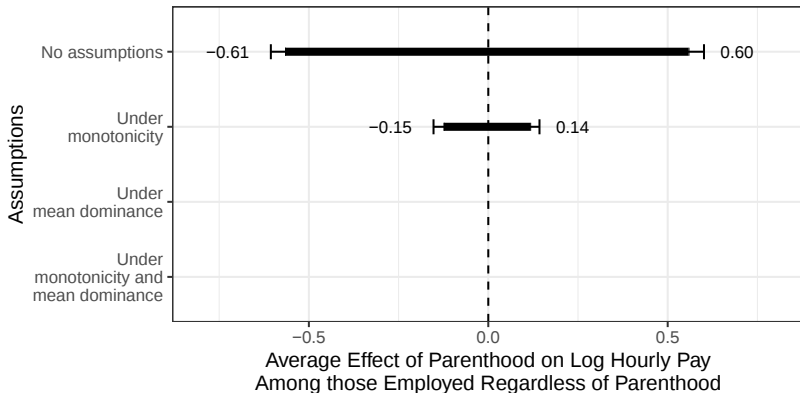
Results: Effect of motherhood on wages



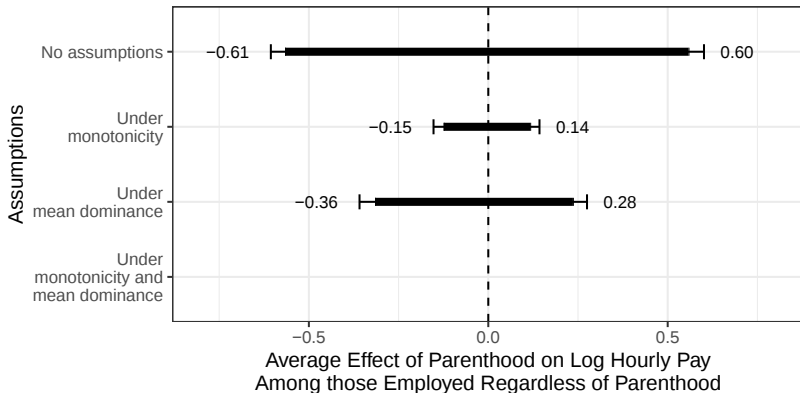
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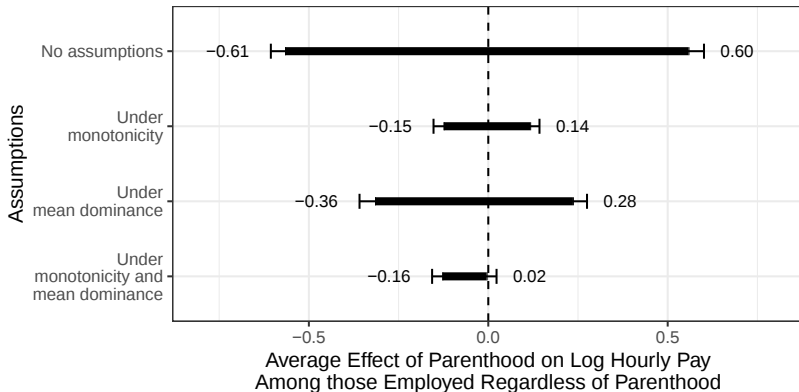
Results: Effect of motherhood on wages



Results: Effect of motherhood on wages



Results: Effect of motherhood on wages



Discussion: Building on past work

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When you can't point-identify,
make assumptions to set-identify

(Manski 1995, 2003)

Discussion: Building on past work

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make assumptions to set-identify (Manski 1995, 2003)

Principal stratification already did this (Frangakis & Rubin 2002)

Discussion: Building on past work

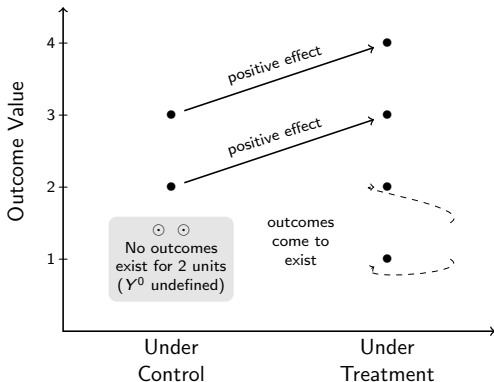
When you can't point-identify,
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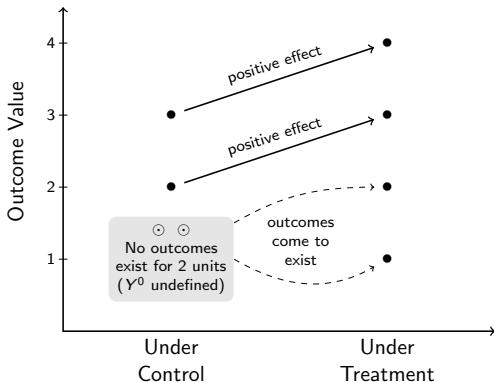
Our new piece:

Regression + simulation for observational studies
with measured confounders

In social stratification,
many causes of outcome values
may also shape outcome existence



In social stratification,
many causes of outcome values
may also shape outcome existence



Thanks!

Ian Lundberg
ianlundberg@ucla.edu

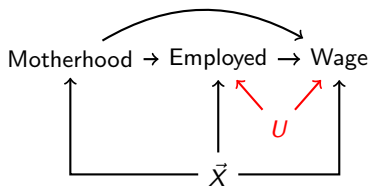
Soonhong Cho
tsehdtm@gmail.com

Draft of paper
[tinyurl.com/
nonexistentoutcomes](https://tinyurl.com/nonexistentoutcomes)

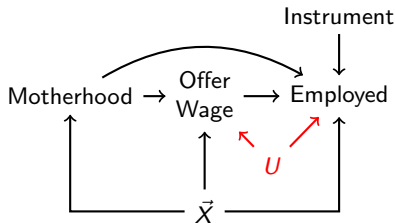
R package
[ilundberg.github.io/
pstratreg](https://ilundberg.github.io/pstratreg)

Appendix Slides

Differences from Heckman selection model



Our DAG



Heckman DAG