Non-existent outcomes in research on inequality

A causal approach

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Cornell Inequality
Discussion Group
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Replication code here

Try our (beta) R package! ilundberg.github.io/pstratreg

Idea

Outcomes that do not exist can hide inequality

Plan

- ▶ one concrete setting
- ► general methodological tools
- ► open questions

Parenthood reduces hourly wages for women

► Budig & England 2001; Gough & Noonan 2013

and increases wages for men

► Killewald 2013; Yu & Hara 2021

Parenthood reduces hourly wages for women

► Budig & England 2001; Gough & Noonan 2013

and increases wages for men

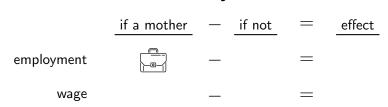
► Killewald 2013; Yu & Hara 2021

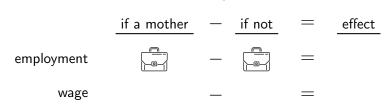
The motherhood wage penalty may be disappearing over time

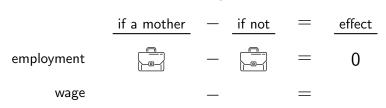
► Pal & Waldfogel 2016; Buchmann & McDaniel 2016; but see Jee et al. 2019

if a mother - if not = effect

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





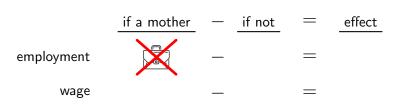


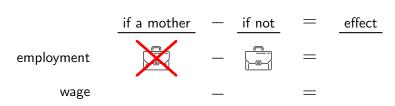


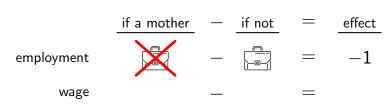
	if a mother	_	if not	=	effect
employment		_		=	0
wage	\$30	_	\$40	=	

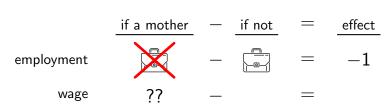
	if a mother	_	if not	=	effect
employment		_		=	0
wage	\$30	_	\$40	=	-\$10

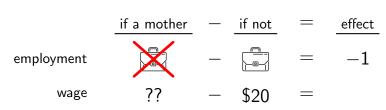
	if a mother	- if not	=	effect
employment		_	=	
wage		_	=	

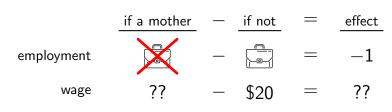












	if a mother	_	if not	=	effect
employment		_		=	-1
wage	??	_	\$20	=	??

Principal Stratification

Frangakis & Rubin 2002; Zhang & Rubin 2003 For an intro, see Miratrix et al. 2018

if a mother	_	if not	=	effect
	_		=	0
\$30	_	\$40	=	-\$10

IVIIa

if a mother
$$-$$
 if not $=$ effect

 $=$ -1

?? $-$ \$20 $=$??



if a mother — if not = effect

if a mother

Nancy

if not

\$30

- \$40 = -\$10

\$30 - \$40 = -\$10

= effect

if a mother — <u>if not</u>

Mia

= effect

if a mother

- if not

- \$20 =

Nia

- \$20 =

if a mother	_	if not	=	effect
	_		=	0

\$30 - \$40 = -\$10

Nancy is a Non-Mother

f a mother	_	if not	=	effect
	_		=	0
\$30	_	\$40	=	-\$10

Mia is a Mother

iviia is	a i	viotn	er		
if a mother	_	if not	=	effect	
	_		=	-1	
??	_	\$20	=	??	

Nia is a Non-Mother



if a mother	_		=	effect
	_		=	
\$30	_	\$40	=	-\$10

Mia is a Mother

Nancy is a Non-Mother

	_	if not	=	effect
	_		=	
\$30	_	\$40	=	-\$10

Nia is a Non-Mother

if a mother	_	if not	=	effect
	-		=	-1
	_	\$20	=	

if a mother	_		=	effect
	_		=	
\$30	_	\$40	=	-\$10

Mia is a Mother



Nancy is a Non-Mother

	_	if not	=	effect
	_		=	
\$30	_	\$40	=	-\$10

Nia is a Non-Mother

if a mother	_	if not	=	effect
	_		=	-1
	_	\$20	=	

Mia is a Mother



Average Observed

\$30

Nancy is a Non-Mother

Nia is a Non-Mother

Average Observed

\$30

if a mother	_		=	effect
	_		=	
\$30	_	\$40	=	-\$10

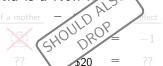
Mia is a Mother



Nancy is a Non-Mother

	_	if not	=	effect
	_		=	
\$30	_	\$40	=	-\$10

Nia is a Non-M



subgroup: always employed

Maya is a Mother

if a mother

Nancy is a Non-Mother

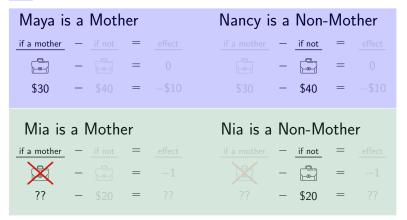
Mia is a Mother



Nia is a Non-M



subgroup: always employed



subgroup: motherhood blocks employment

Goal Motherhood wage effect among the always-employed

	Mother?	Wage	
Maya	Yes	\$30	
Mia	Yes	??	
Nancy	No	\$40	
Nia	No	\$20	

	Mother?	Wage	
Maya	Yes	\$30	
Mia	Yes	??	
Nancy	No	\$40	
Nia	No	\$20	

Mother? Wage

Maya Yes \$30

Mia Yes ??

Nancy No \$40

Nia No \$20

and would be employed if not

women who would be employed if a mom

Assumption.

Employed mothers would still be employed even if they had no children

Mother? Wage

Maya Yes \$30

Mia Yes ??

Nancy No \$40

Nia No \$20

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Mother? Wage

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Nancy No \$40

Nia No \$20

women who would be employed if a mom and would be employed if not

Assumption.

Employed mothers would still be employed even if they had no children

Bound.

Report the highest and lowest estimates consistent with the data

Estimated Effect of Motherhood

Upper Bound

Lower Bound:

		Mother?	Wage
	Maya	Yes	\$30
	Mia	Yes	??
	Nancy	No	\$40
	Nia	No	\$20

women who would be employed if a mom and would be employed if not

Assumption.

Employed mothers would still be employed even if they had no children

Bound.

Report the highest and lowest estimates consistent with the data

Estimated Effect of Motherhood

Upper Bound: +\$10 Lower Bound:

	Mother?	Wage
Maya	Yes	\$30
- Mia	Yes	??
Nancy	No	\$40
Nia	No	\$20

women who would be employed if a mom and would be employed if not

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Report the highest and lowest estimates consistent with the data

Estimated Effect

Upper Bound: +\$10Lower Bound: -\$10

Mother? Wage

Maya Yes \$30

Mia Yes ??

Nancy No \$40

Nia No \$20

women who
would be employed if a mom
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Assumption.

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Bound.

Report the highest and lowest estimates consistent with the data

Estimated Effect of Motherhood

Upper Bound: +\$10

Lower Bound: -\$10

In practice,

► motherhood is not randomized

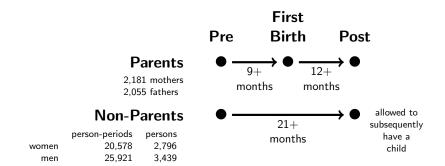
▶ identical people do not exist

Our contribution: Model-based estimates

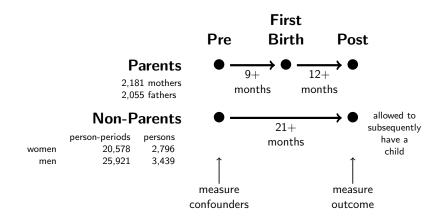
Data: NLSY97



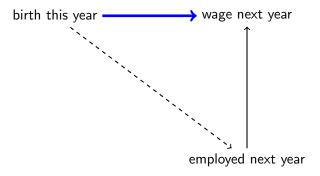
Data: NLSY97

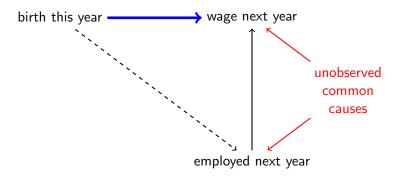


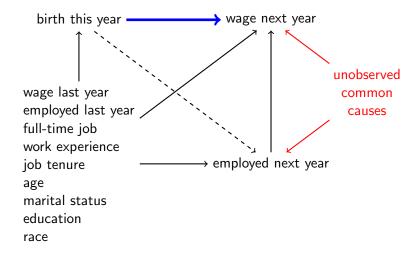
Data: NLSY97



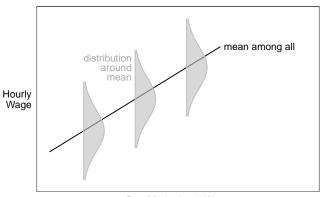
birth this year — wage next year



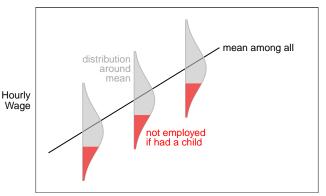




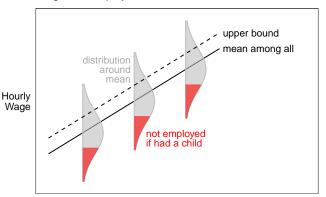
- 1. Logit of employment given motherhood and confounders
 - Estimate the proportion always-employed at each \vec{X} , \vec{A}
- 2. OLS model of wage given motherhood and confounders
 - ► Predict wage under motherhood (no modifications)
 - ► Predict wage under no motherhood (with bounding)



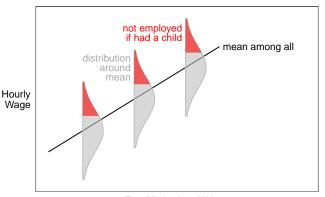
Pre-Motherhood Wage



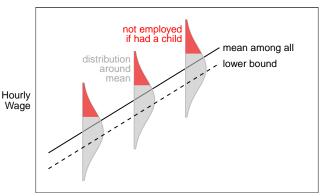
Pre-Motherhood Wage



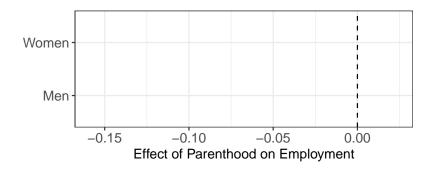
Pre-Motherhood Wage

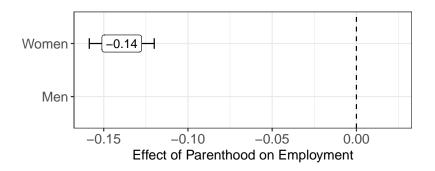


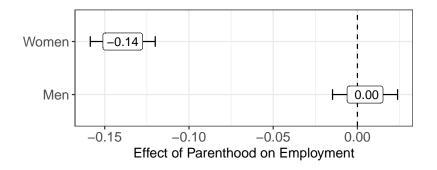
Pre-Motherhood Wage

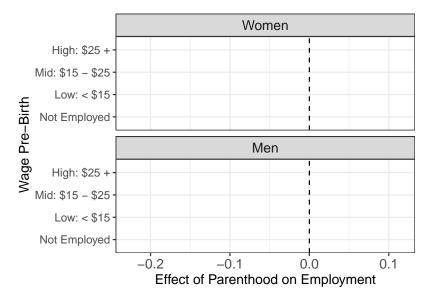


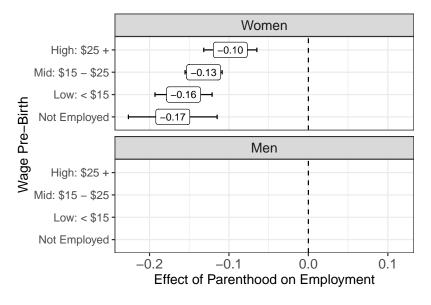
Pre-Motherhood Wage

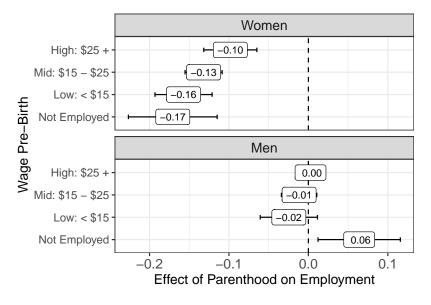


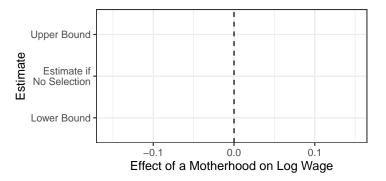


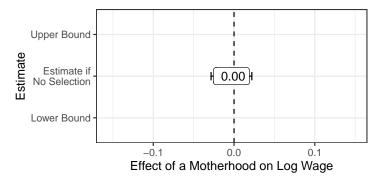


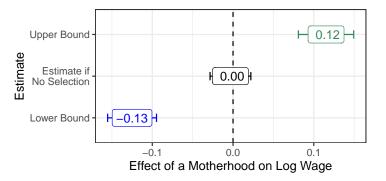


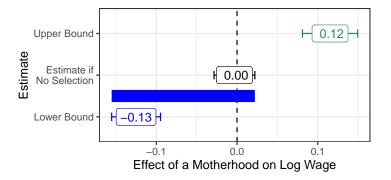




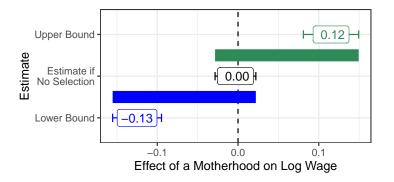




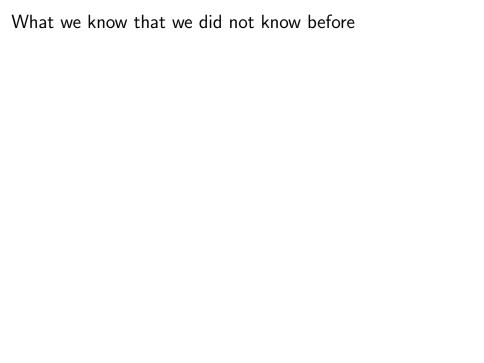




If you believe the **lowest**-earning non-mothers would stop paid employment if they had a child



If you believe the **lowest**-earning or **highest**-earning non-mothers would stop paid employment if they had a child



We knew in recent years, motherhood only weakly predicts pay*

We knew in recent years, motherhood only weakly predicts pay*

*among the employed

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This fact is consistent with two stories

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This fact is consistent with two stories

1. motherhood's causal effect on pay is small

We knew in recent years, motherhood only weakly predicts pay*

*among the employed

This fact is consistent with two stories

1. motherhood's causal effect on pay is small

or

2. employed non-mothers the wrong comparison population

We knew in recent years, motherhood only weakly predicts pay*

*among the employed

This fact is consistent with two stories

1. motherhood's causal effect on pay is small

or

- 2. employed non-mothers the wrong comparison population
 - ▶ lowest-earning non-mothers might stop paid work with a child

We know how to think about outcomes that **don't exist**

We know how to think about outcomes that **don't exist**

$$=$$
 -1 $?? - $25 = ??$

We know how to think about outcomes that **don't exist**



in the labor market
— some people are not employed

We know how to think about outcomes that don't exist



in the labor market
— some people are not employed
in intergenerational mobility
— some people have no kids

We know how to think about outcomes that **don't exist**



in the labor market
— some people are not employed
in intergenerational mobility
— some people have no kids

in assortative mating— some people have no spouse

We know how to think about outcomes that **don't exist**





in the labor market
— some people are not employed
in intergenerational mobility
— some people have no kids

in assortative mating
— some people have no spouse

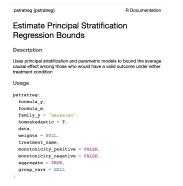
We know how to think about outcomes that **don't exist**





in the labor market

- some people are not employed
- in intergenerational mobility
 some people have no kids
- in assortative mating
 - some people have no spouse



Appendix

Sample restrictions: Persons

Mothers	Non-Mothers	Fathers	Non-Fathers
2,999	3,746	2,662	4,200
2,315	2,832	2,273	3,522
2,098	2,830	2,029	3,517
1,985	2,794	1,837	3,436
	Mothers 2,999 2,315 2,098 1,985	2,999 3,746 2,315 2,832 2,098 2,830	2,999 3,746 2,662 2,315 2,832 2,273 2,098 2,830 2,029

^{*} Requirement is

▶ parents: observed at

▶ pre-birth: 3 years to 9 months before

▶ post-birth: 1–3 years after

► for non-parents, two observations

▶ at least 1 year + 9 months apart

▶ no more than 6 years apart

Sample restrictions: Person-Periods

Mothers	Non-Mothers	Fathers	Non-Fathers
2,999	31,510	2,662	39,325
2,315	21,743	2,273	28,159
2,098	21,704	2,029	29,135
1,985	20,543	1,837	25,902
		2,999 31,510 2,315 21,743 2,098 21,704	2,999 31,510 2,662 2,315 21,743 2,273 2,098 21,704 2,029

^{*} Requirement is

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► for non-parents, two observations

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▶ no more than 6 years apart

Variable definitions

- ► A treatment: first birth occurs
- ► Y outcome: log hourly wage in 2022 dollars
 - including tips, overtime bonuses
 - ► includes non-hourly workers
 - ► for the job current at interview date
- $ightharpoonup \vec{X}$ confounders
 - ► log(wage in pre-period)
 - ► employed in pre-period
 - ▶ full time (35+ hours) in pre-period current job
 - ightharpoonup log(years of full-time work experience + 1), from weekly arrays
 - $ightharpoonup \log(\text{years of tenure in current job} + 1)$, from job roster
 - ▶ age + age squared
 - ► marital status (married with spouse present, cohabiting, other)
 - education (less than high school, high school degree, 2-year college degree, 4-year college degree)
 - ► race (Hispanic, non-Hispanic Black, other)

Statistical models: Mediator (employment)

 $egin{aligned} A & \text{indicates parenthood} \ M = 1 & \text{indicates employment} \ ec{X} & \text{are confounders} \end{aligned}$

$$\operatorname{logit}\left(P(\textit{M}=1\mid\vec{X},\textit{A})\right) = \alpha + \vec{X}'\vec{\gamma} + \textit{A}\left(\beta + \vec{X}'\vec{\eta}\right)$$

Conditional average effect on mediator (employment)

$$\begin{split} \hat{P}(M^1 = 1 \mid \vec{X}, A) &= \mathsf{logit}^{-1} \left(\hat{\alpha} + \vec{X}' \hat{\vec{\gamma}} + 1 \times \left(\hat{\beta} + \vec{X}' \hat{\vec{\eta}} \right) \right) \\ \hat{P}(M^0 = 1 \mid \vec{X}, A) &= \mathsf{logit}^{-1} \left(\hat{\alpha} + \vec{X}' \hat{\vec{\gamma}} + 0 \times \left(\hat{\beta} + \vec{X}' \hat{\vec{\eta}} \right) \right) \end{split}$$

Conditional Average Effect = Top - Bottom

Statistical models: Outcome (wage)

A indicates parenthood. M=1 indicates employment. Y is log hourly wage. \vec{X} are confounders.

$$\begin{split} Y \mid \vec{X}, A, M &= 1 \sim \mathsf{Normal}\left(\mu(\vec{X}, A), \sigma^2(\vec{X}, A)\right) \\ \mu\left(\vec{X}, A\right) &= \lambda + \vec{X}'\vec{\nu} + A\left(\tau + \vec{X}'\vec{\delta}\right) \\ \log\left[\sigma^2\left(\vec{X}, A\right)\right] &= \xi + \vec{X}'\vec{\psi} + A\omega \end{split}$$

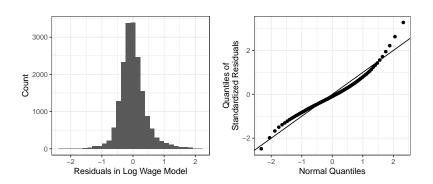
Estimate by

- for $\mu(\vec{X}, A)$, estimate by OLS with Y as the outcome
- ▶ then we calculate the residual $\hat{\epsilon} = Y \hat{Y}$
- ▶ for $\sigma^2(\vec{X}, A)$, estimate by Gamma GLM with a log link with $\hat{\epsilon}^2$ as the outcome (Western & Bloome 2009)

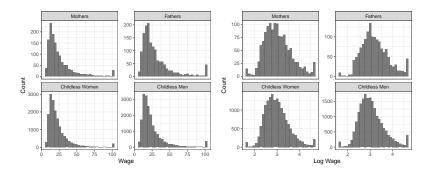
Statistical models: Effects on wage

- 1. At the \vec{X} of each unit, simulate
 - $\begin{array}{l} \blacktriangleright \quad Y^1 \sim \operatorname{Normal}\left(\mu(\vec{X},A=1),\sigma^2(\vec{X},A=1)\right) \\ \blacktriangleright \quad Y^0 \sim \operatorname{Normal}\left(\mu(\vec{X},A=0),\sigma^2(\vec{X},A=0)\right) \end{array}$
- 2. Remove the upper (lower) portion at this \vec{X} value estimated to be the not-always-employed
- Estimate the mean of the simulated values
- 4. Repeat for every unit

Normality of residuals



Histogram: Wage



Alternative: Utility functions

Alternative solution: Code the unemployed people with a wage

▶ if unemployed, then code with minimum wage

This works if you believe a utility function

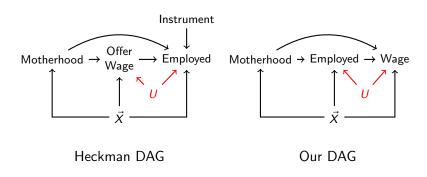
$$U = \begin{cases} \log (\min \text{ wage}) & \text{if not employed} \\ \log (\text{wage}) & \text{if employed} \end{cases}$$

But if it is just a convenience

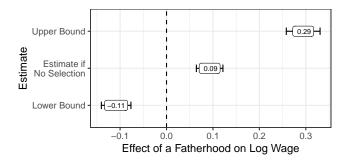
- ▶ then it does not bound effects on *Y*
- ▶ you might miss the real story
 - ▶ if half the sample was not employed, would you do this?

Alternative: Heckman selection

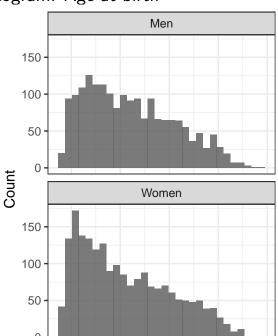
Premise: Everyone has a wage offer. Non-employed don't take it. Goal: Infer about everyone, despite sample selection.



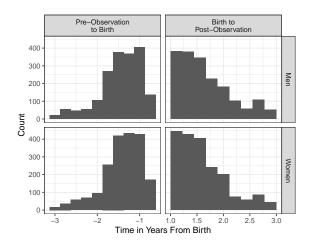
Fatherhood effects



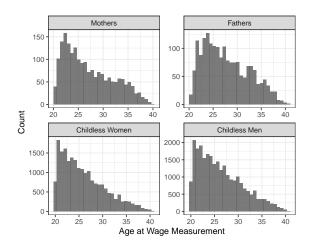
Histogram: Age at birth



Histogram: Observation timing around birth



Histogram: Age of wage measurement



Histogram: Year of wage measurement

