

# Bounding the Child Penalty

Julius Ilciukas

University of Amsterdam

# Motivation

Children may be the main reason behind gender gaps in the labor market.

# Motivation

Children may be the main reason behind gender gaps in the labor market.

- ▶ Public discourse:
  - ▶ The New York Times: “The Gender Pay Gap Is Largely Because of Motherhood” (C. C. Miller, 2017)
  - ▶ Business Insider: “What’s the major reason a woman might get paid less than men in the same field, and with the same education? Kids.” (Kaplan, 2023)

# Motivation

Children may be the main reason behind gender gaps in the labor market.

- ▶ Public discourse:
  - ▶ The New York Times: “The Gender Pay Gap Is Largely Because of Motherhood” (C. C. Miller, 2017)
  - ▶ Business Insider: “What’s the major reason a woman might get paid less than men in the same field, and with the same education? Kids.” (Kaplan, 2023)
- ▶ Academic discourse:
  - ▶ “Not surprisingly, children are the main contributors to women’s labor supply changes.” (Goldin, 2014)
  - ▶ “The effects of parenthood ( . . . ) account for most of the observed gender inequality in labor market outcomes” (Kleven et al., 2023)

# Identification Challenge

# Identification Challenge

Fertility is endogenous

- ▶ Human capital, wealth, health, career prospects, the cost of parenthood

# Identification Challenge

Fertility is endogenous

- ▶ Human capital, wealth, health, career prospects, the cost of parenthood

Effects of parenthood are dynamic

- ▶ Time spent in parenthood, number and age of children, career stage at and during parenthood

# Identification Challenge

Fertility is endogenous

- ▶ Human capital, wealth, health, career prospects, the cost of parenthood

Effects of parenthood are dynamic

- ▶ Time spent in parenthood, number and age of children, career stage at and during parenthood

**Leading methods only addresses each separately**



## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

All mothers for 5 years

Age 35,  
1st child at 36

All childless

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

Age 35,  
1st child at 36

**All childless**

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

Age 35,  
1st child at 36

**All childless**

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

Age 35,  
1st child at 36

**All childless**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Søgaaard, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

Age 35,  
1st child at 36

**All childless**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

IV-IVF (Lundborg et al., 2017):

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

Age 35,  
1st child at 36

**All childless**

IV-IVF (Lundborg et al., 2017):

Age 35,  
1st IVF at 30 worked

All mothers for 5 years

Age 35,  
1st IVF at 30 failed

Some childless, some  
mothers for <5 years

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

Age 35,  
1st child at 36

**All childless**

IV-IVF (Lundborg et al., 2017):

Age 35,  
**1st IVF at 30 worked**

All mothers for 5 years

Age 35,  
**1st IVF at 30 failed**

Some childless, some  
mothers for <5 years



## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

Age 35,  
1st child at 36

**All childless**

IV-IVF (Lundborg et al., 2017):

Age 35,  
**1st IVF at 30 worked**

All mothers for 5 years

Age 35,  
**1st IVF at 30 failed**

Some childless, some  
mothers for <5 years

## ES and IV-IVF

“Some of the most compelling evidence of the crucial role children (...) has been produced over the past few years” (Bertrand, 2020)

Event study (Kleven, Landais, & Sørensen, 2019):

Age 35,  
1st child at 30

**All mothers for 5 years**

- Not a TWFE-staggered rollout problem (Melentyeva & Riedel, 2023)

Age 35,  
1st child at 36

**All childless**

IV-IVF (Lundborg et al., 2017):

Age 35,  
**1st IVF at 30 worked**

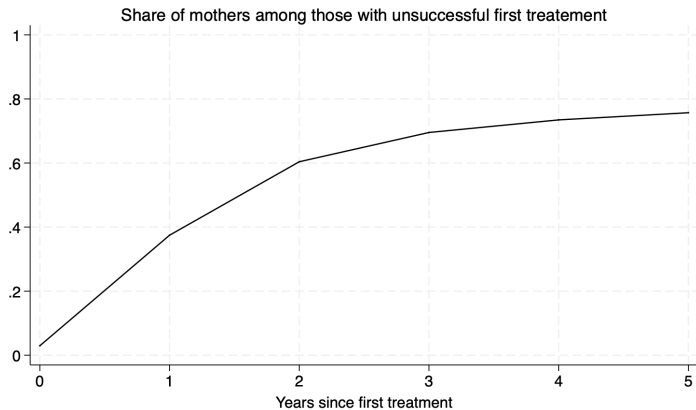
All mothers for 5 years

Age 35,  
**1st IVF at 30 failed**

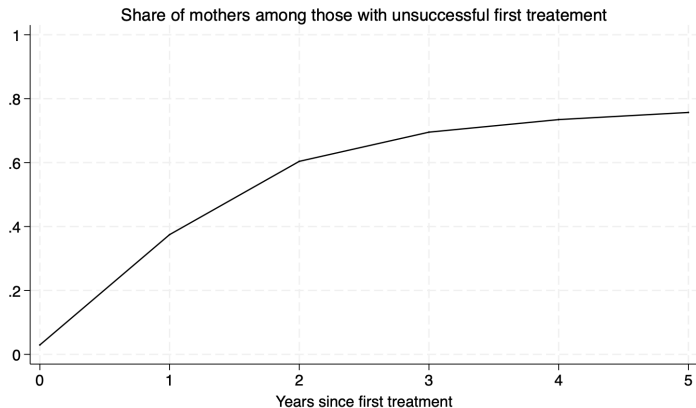
Some childless, some  
mothers for <5 years

**Very different results even in same samples** My sample

# Motherhood Among Unsuccessfully Treated

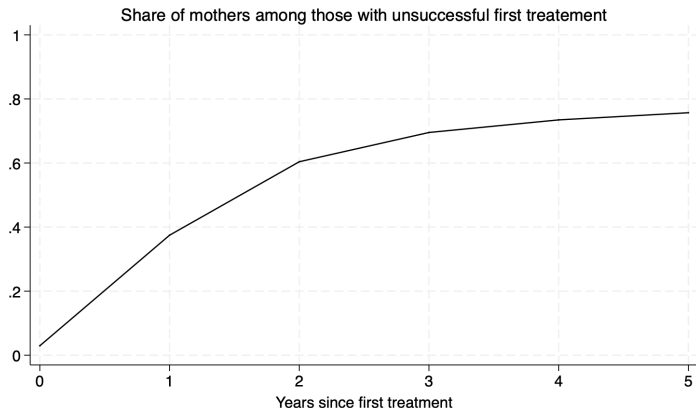


# Motherhood Among Unsuccessfully Treated



$$\tau_{RF} = 0.25\tau_{Parenthood} - 0.75\tau_{Delay}$$

# Motherhood Among Unsuccessfully Treated



$$\tau_{RF} = 0.25\tau_{Parenthood} - 0.75\tau_{Delay}$$

$$\tau_{IV} = \tau_{Parenthood} - 3\tau_{Delay}$$

How much can we say about the causal effect of  
parenthood?

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
  2. Empirical evidence using Dutch data
- Minimal assumptions → see what is possible



# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data
  - ▶ Minimal assumptions → see what is possible
  - ▶ Only crucial assumption: randomness in IVF success
    - ▶ Endogenous number of attempts
    - ▶ Endogenous non-IVF fertility
    - ▶ No restrictions on effects
      - ▶ Bensnes et al. (2023); Gallen et al. (2023) Testing restrictions

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data
  - ▶ Minimal assumptions → see what is possible
  - ▶ Only crucial assumption: randomness in IVF success
    - ▶ Endogenous number of attempts
    - ▶ Endogenous non-IVF fertility
    - ▶ No restrictions on effects
      - ▶ Bensnes et al. (2023); Gallen et al. (2023) Testing restrictions
  - ▶ Identification approach:
    - ▶ Clean comparison: baseline-mothers vs childless
    - ▶ Exploit whole sequence of IVF attempts to handle IVF births
    - ▶ Bounds to handle non-IVF births

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data
  - ▶ Minimal assumptions → see what is possible
  - ▶ Only crucial assumption: randomness in IVF success
    - ▶ Endogenous number of attempts
    - ▶ Endogenous non-IVF fertility
    - ▶ No restrictions on effects
      - ▶ Bensnes et al. (2023); Gallen et al. (2023) Testing restrictions
  - ▶ Identification approach:
    - ▶ Clean comparison: baseline-mothers vs childless
    - ▶ Exploit whole sequence of IVF attempts to handle IVF births
    - ▶ Bounds to handle non-IVF births
  - ▶ Narrowing bounds
    - ▶ Adapted DML estimator of Semenova (2020)

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data
  - ▶ Minimal assumptions → see what is possible
  - ▶ Only crucial assumption: randomness in IVF success
    - ▶ Endogenous number of attempts
    - ▶ Endogenous non-IVF fertility
    - ▶ No restrictions on effects
      - ▶ Bensnes et al. (2023); Gallen et al. (2023) Testing restrictions
  - ▶ Identification approach:
    - ▶ Clean comparison: baseline-mothers vs childless
    - ▶ Exploit whole sequence of IVF attempts to handle IVF births
    - ▶ Bounds to handle non-IVF births
  - ▶ Narrowing bounds
    - ▶ Adapted DML estimator of Semenova (2020)
  - ▶ Application to Dutch data

# This Paper

1. Estimator that simultaneously addresses endogenous timing and dynamic effects
2. Empirical evidence using Dutch data
  - ▶ Minimal assumptions → see what is possible
  - ▶ Only crucial assumption: randomness in IVF success
    - ▶ Endogenous number of attempts
    - ▶ Endogenous non-IVF fertility
    - ▶ No restrictions on effects
      - ▶ Bensnes et al. (2023); Gallen et al. (2023) Testing restrictions
  - ▶ Identification approach:
    - ▶ Clean comparison: baseline-mothers vs childless
    - ▶ Exploit whole sequence of IVF attempts to handle IVF births
    - ▶ Bounds to handle non-IVF births
  - ▶ Narrowing bounds
    - ▶ Adapted DML estimator of Semenova (2020)
  - ▶ Application to Dutch data
    - ▶ Sizable effect on women's outcomes in short-medium run
    - ▶ Explains up to half of post-child gender inequality
    - ▶ Both event study and IV might overstate the career cost

# Model

# Model

- ▶ Time starts at first attempt

# Model

- ▶ Time starts at first attempt
- ▶ Each moment of entering motherhood associated with different potential outcome:



# Model

- ▶ Time starts at first attempt
- ▶ Each moment of entering motherhood associated with different potential outcome:

$$Y_t(1), Y_t(2), \dots, Y_t(T).$$

# Model

- ▶ Time starts at first attempt
- ▶ Each moment of entering motherhood associated with different potential outcome:

$$Y_t(1), Y_t(2), \dots, Y_t(T).$$

- ▶ Childless outcome:

$$Y_t(0).$$

# Model

- ▶ Time starts at first attempt
- ▶ Each moment of entering motherhood associated with different potential outcome:

$$Y_t(1), Y_t(2), \dots, Y_t(T).$$

- ▶ Childless outcome:

$$Y_t(0).$$

For simplicity we are at  $t = T$ .

## Model (cont.)

## Model (cont.)

Women differ in:

- ▶ How many IVF attempts would undergo if all fail (integer  $G$ )?

## Model (cont.)

Women differ in:

- ▶ How many IVF attempts would undergo if all fail (integer  $G$ )?
- ▶ Would enter motherhood if all attempts failed (dummy  $N$ )?
  - ▶  $\sim$  “always-takers”

## Model (cont.)

Women differ in:

- ▶ How many IVF attempts would undergo if all fail (integer  $G$ )?
- ▶ Would enter motherhood if all attempts failed (dummy  $N$ )?
  - ▶  $\sim$  “always-takers”
- ▶ **Both are endogenous but independent of success:**

## Model (cont.)

Women differ in:

- ▶ How many IVF attempts would undergo if all fail (integer  $G$ )?
- ▶ Would enter motherhood if all attempts failed (dummy  $N$ )?
  - ▶  $\sim$  “always-takers”
- ▶ **Both are endogenous but independent of success:**

$$(Y(1), Y(0), N, G) \perp D_j | P \geq j$$

- ▶  $P$  - number of attempts
- ▶  $D_j$  - success of attempt  $j$

**“Once sperm/eggs at attempt  $j$  are implanted, whether this results in a conception is as-good-as-random”**



## Model (cont.)

Women differ in:

- ▶ How many IVF attempts would undergo if all fail (integer  $G$ )?
- ▶ Would enter motherhood if all attempts failed (dummy  $N$ )?
  - ▶  $\sim$  “always-takers”
- ▶ **Both are endogenous but independent of success:**

$$(Y(1), Y(0), N, G) \perp D_j | P \geq j$$

- ▶  $P$  - number of attempts
- ▶  $D_j$  - success of attempt  $j$

**“Once sperm/eggs at attempt  $j$  are implanted, whether this results in a conception is as-good-as-random”**

Object of interest:

$$\tau_C = \mathbb{E}[Y(1) - Y(0) | N = 0]$$

Effect of motherhood for women reliant on treatments to conceive.

Simple World: Max 1 Attempt, Conception Only via IVF

## Simple World: Max 1 Attempt, Conception Only via IVF

$$G = 1$$

(willing to try once)

## Simple World: Max 1 Attempt, Conception Only via IVF

$G = 1$   
(willing to try once)

$$D_1 = 1$$

$$D_1 = 0$$

## Simple World: Max 1 Attempt, Conception Only via IVF

$G = 1$   
(willing to try once)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)]$$

$$D_1 = 0$$

$$\mathbb{E}[Y(0)]$$

Simple World: Max 2 Att., Only via IVF (**if G Obs.**)

## Simple World: Max 2 Att., Only via IVF (**if G Obs.**)

$$G = 1$$

(willing to try once)

$$D_1 = 1$$

$$D_1 = 0$$

## Simple World: Max 2 Att., Only via IVF (if **G Obs.**)

$$G = 1$$

(willing to try once)

$$D_1 = 1$$

$$D_1 = 0$$

$$G = 2$$

(willing to try twice)

$$D_1 = 1$$

$$D_1 = 0, D_2 = 1$$

$$D_1 = 0, D_2 = 0$$



## Simple World: Max 2 Att., Only via IVF (if **G Obs.**)

$$G = 1$$

(willing to try once)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)|G = 1]$$

$$D_1 = 0$$

$$\mathbb{E}[Y(0)|G = 1]$$

$$G = 2$$

(willing to try twice)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)|G = 2]$$

$$D_1 = 0, D_2 = 1$$

$$\mathbb{E}[Y(\textit{later})|G = 2]$$

$$D_1 = 0, D_2 = 0$$

$$\mathbb{E}[Y(0)|G = 2]$$

## Simple World: Max 2 Att., Only via IVF (Observed)

$$G = 1$$

(willing to try once)

$$G = 2$$

(willing to try twice)

$$D_1 = 1$$

$$D_1 = 0$$

$$D_1 = 0, D_2 = 1$$

$$D_1 = 0, D_2 = 0$$

## Simple World: Max 2 Att., Only via IVF (Observed)

$$G = 1$$

(willing to try once)

$$G = 2$$

(willing to try twice)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)]$$

$$D_1 = 0$$

$$\mathbb{E}[Y(0)|G = 1]$$

$$D_1 = 0, D_2 = 1$$

$$\mathbb{E}[Y(\textit{later})|G = 2]$$

$$D_1 = 0, D_2 = 0$$

$$\mathbb{E}[Y(0)|G = 2]$$

## Simple World: Max 2 Att., Only via IVF (Observed)

$$G = 1$$

(willing to try once)

$$G = 2$$

(willing to try twice)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)]$$

$$D_1 = 0$$

$$\mathbb{E}[Y(0)|G = 1]$$

$$D_1 = 0, D_2 = 1$$

$$\mathbb{E}[Y(\textit{later})|G = 2]$$

$$D_1 = 0, D_2 = 0$$

$$\mathbb{E}[Y(0)|G = 2]$$

# Simple World: Max 2 Att., Only via IVF (Observed)

$G = 1$   
(willing to try once)

$G = 2$   
(willing to try twice)

$$D_1 = 1$$

$$\mathbb{E}[Y(1)]$$

$$D_1 = 0$$

$$\mathbb{E}[Y(0)|G = 1]$$

$$D_1 = 0, D_2 = 1$$

$$\mathbb{E}[Y(\text{later})|G = 2]$$

$$Pr(G = 1) =$$

$$D_1 = 0, D_2 = 0$$

$$\mathbb{E}[Y(0)|G = 2]$$

## Simple World: Max 1 Attempt and Non-IVF

## Simple World: Max 1 Attempt and Non-IVF

$$G = 1$$

$$N = 0$$

(no child if fail)

$$N = 1$$

(child if fail)

## Simple World: Max 1 Attempt and Non-IVF

$$G = 1$$

$$N = 0$$

(no child if fail)

$$N = 1$$

(child if fail)

$$D_1 = 1$$



## Simple World: Max 1 Attempt and Non-IVF

$$G = 1$$

$N = 0$   
(no child if fail)

$N = 1$   
(child if fail)

$$D_1 = 1$$

$$D_1 = 0, C = 0$$

$$D_1 = 0, C = 1$$

## Simple World: Max 1 Attempt and Non-IVF

$$G = 1$$

$N = 0$   
(no child if fail)

$N = 1$   
(child if fail)

$$D_1 = 1$$

$$F_{Y(1)}$$

$$D_1 = 0, C = 0$$

$$\mathbb{E}[Y(0)|N = 0]$$

$$D_1 = 0, C = 1$$

$$\mathbb{E}[Y(\textit{later})|N = 1]$$

# Simple World: Max 1 Attempt and Non-IVF

$$G = 1$$

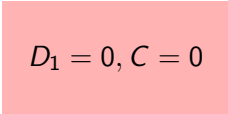
$N = 0$   
(no child if fail)

$N = 1$   
(child if fail)


$$D_1 = 1$$

$F_{Y(1)}$

---


$$D_1 = 0, C = 0$$

$$\mathbb{E}[Y(0)|N = 0]$$

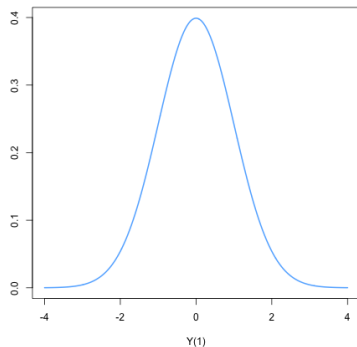

$$D_1 = 0, C = 1$$

$$\mathbb{E}[Y(later)|N = 1]$$

$$Pr(N = 0) = \frac{\text{red square}}{\text{red square} + \text{gray square}}$$

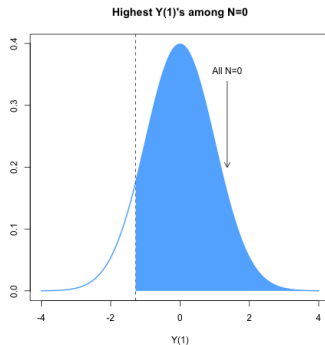
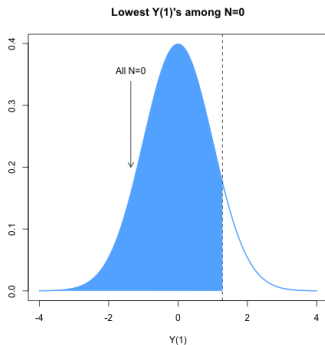
# Intuition: Motherhood Outcome $Y(1)$

1. Identify distribution of motherhood outcomes using women with successful first treatment



# Intuition: Motherhood Outcome $Y(1)$ (cont.)

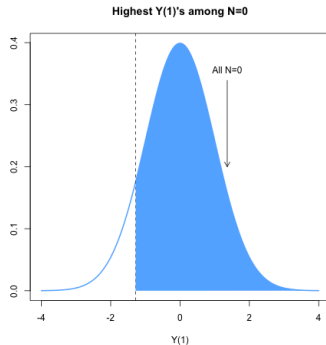
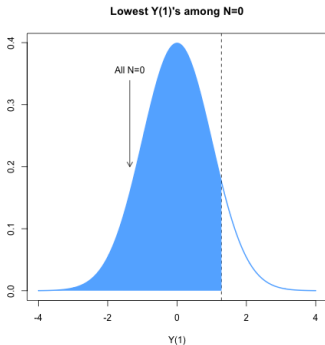
2. Estimate  $\Pr(N = 0) = 0.9$  on control group
3. Assume most extreme distributions of types



# Intuition: Motherhood Outcome $Y(1)$ (cont.)

4. The means of the two trimmed distributions give bounds:

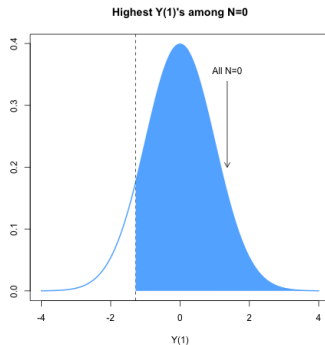
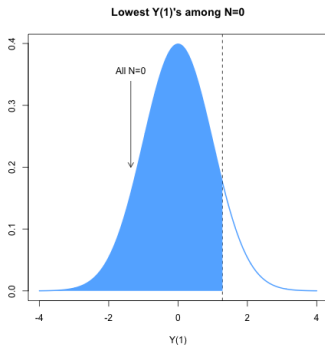
$$LB_{\mathbb{E}[Y(1)|N=0]} \leq \mathbb{E}[Y(1)|N=0] \leq UB_{\mathbb{E}[Y(1)|N=0]}$$



# Intuition: Motherhood Outcome $Y(1)$ (cont.)

## 5. Bounds on the effect:

$$LB_{\tau_c} \leq \mathbb{E}[Y(1) - Y(0) | N = 0] \leq UB_{\tau_c}$$



Using covariates

Estimator

# Assisted Fertility Treatments



# Assisted Fertility Treatments

## In vitro fertilization (IVF)

- ▶ Relatively invasive procedure performed under sedation/anesthesia
- ▶ ~25% success rate

# Assisted Fertility Treatments

## In vitro fertilization (IVF)

- ▶ Relatively invasive procedure performed under sedation/anesthesia
- ▶ ~25% success rate

## Intrauterine insemination (IUI)

- ▶ Sperm injected directly into the uterus.
- ▶ ~10% success rate
- ▶ First-line infertility treatment in most countries

# Assisted Fertility Treatments

## In vitro fertilization (IVF)

- ▶ Relatively invasive procedure performed under sedation/anesthesia
- ▶ ~25% success rate

## Intrauterine insemination (IUI)

- ▶ Sperm injected directly into the uterus.
- ▶ ~10% success rate
- ▶ First-line infertility treatment in most countries

I exploit the moment embryos/sperm are transferred into the uterus

Is success as-good-as-random?

# Data

- ▶ Administrative data from Statistics Netherlands
  - ▶ Data on fertility treatments from 2013 to 2017
  - ▶ Labor market outcomes from 2011 to 2021

# Data

- ▶ Administrative data from Statistics Netherlands
  - ▶ Data on fertility treatments from 2013 to 2017
  - ▶ Labor market outcomes from 2011 to 2021
- ▶ Unlimited IUI and first 3 IVF attempts covered by mandatory insurance (later IVF attempts cost 2500-5000 Eur per cycle)

# Data

- ▶ Administrative data from Statistics Netherlands
  - ▶ Data on fertility treatments from 2013 to 2017
  - ▶ Labor market outcomes from 2011 to 2021
- ▶ Unlimited IUI and first 3 IVF attempts covered by mandatory insurance (later IVF attempts cost 2500-5000 Eur per cycle)
- ▶ Sample of opposite sex couples cohabiting before first IUI attempt

Balance

Treatment success

Success prob. change

## Results

# Bounds

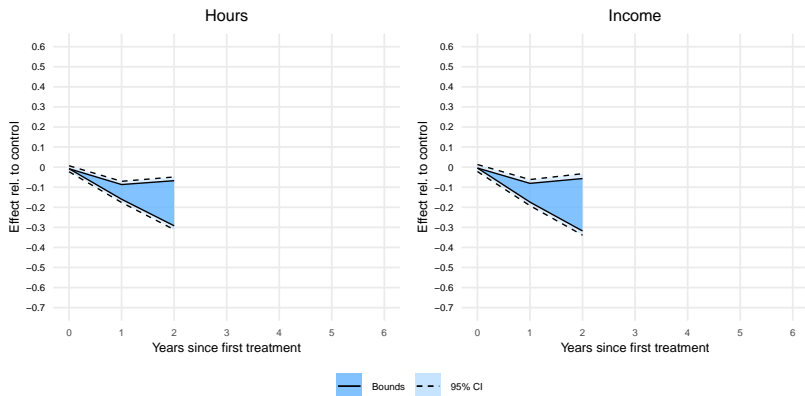


Figure 1: Bounds - short run

Baseline Lee bounds

Absolute effects



# Bounds

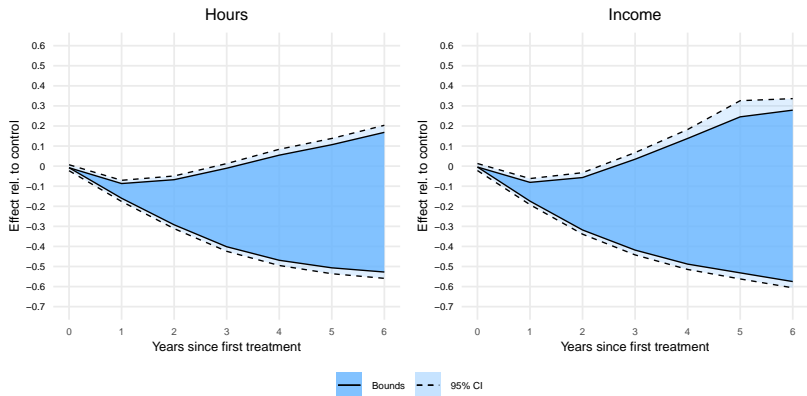


Figure 2: Bounds - medium run

Baseline Lee bounds

Absolute effects

# Monotonicity

# Monotonicity

- ▶ Some women whose first treatment attempt succeeds eventually conceive more children without treatments

# Monotonicity

- ▶ Some women whose first treatment attempt succeeds eventually conceive more children without treatments
- ▶ It may be reasonable to assume that they would have eventually conceived at least one child if all treatments had failed

Plausibility discussion

Benefit of monotonicity

Graphic intuition

# Monotone Bounds

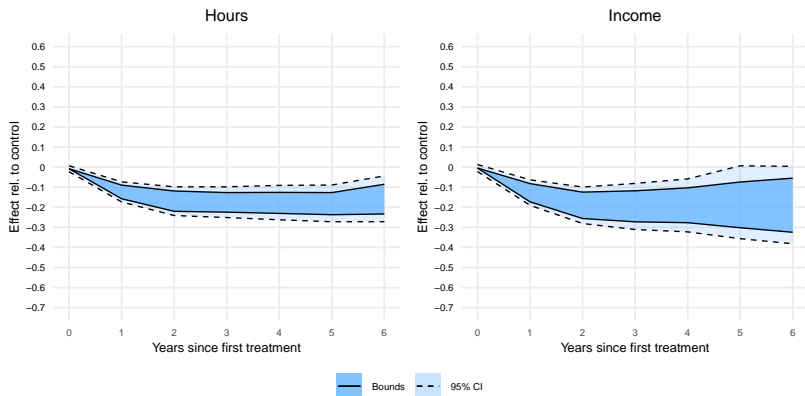


Figure 3: Monotone bounds for percent effects

Absolute

How wide?

# Monotone Bounds: Explaining Gender Inequality

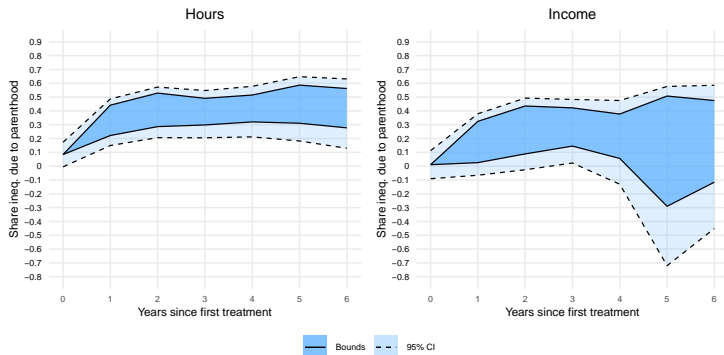


Figure 4: Share of gender inequality explained by parenthood

# Extensions

## Outcomes:

- ▶ Fatherhood Absolute Percentage
- ▶ Decomposing gender inequality Share explained by children
- ▶ Effect of delaying motherhood Absolute Cumulative

## Existing estimators:

- ▶ Are existing estimates biased? IV-IVF equivalent Placebo event Placebo ineq.
- ▶ Are estimates less informative than existing? Confidence intervals

## Robustness:

- ▶ Bias due to depression Effect on depression Bounds for non-depressed
- ▶ Correcting for parental leave Max. leave
- ▶ Inequality correcting for age De-aging partners
- ▶ Stable complier group Childless final period
- ▶ Estimator without DML Identification Effects
- ▶ Relaxing monotonicity Direction Partnered only

## Other:

- ▶ Heterogeneity Covariates Willingness to try
- ▶ Population imputation\* ES pop. vs IVF Mother. imp. Childless imp. Effect imp.

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects



# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years
  - ▶ Under monotonicity: stable after 5 years

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years
  - ▶ Under monotonicity: stable after 5 years
  - ▶ Drives up to 60% (50%) of gender inequality in post-child work hours (earnings)

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years
  - ▶ Under monotonicity: stable after 5 years
  - ▶ Drives up to 60% (50%) of gender inequality in post-child work hours (earnings)
- ▶ Comparison to existing approaches

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years
  - ▶ Under monotonicity: stable after 5 years
  - ▶ Drives up to 60% (50%) of gender inequality in post-child work hours (earnings)
- ▶ Comparison to existing approaches
  - ▶ IV-IVF might overstate penalty in the short run

# Conclusion

- ▶ Estimator for the career cost of children that simultaneously address selective timing and dynamic effects
  - ▶ Can be applied to other settings with dynamic and selective treatment assignment
- ▶ Application to Dutch data:
  - ▶ Sizable career impacts of parenthood in the first two years
  - ▶ Under monotonicity: stable after 5 years
  - ▶ Drives up to 60% (50%) of gender inequality in post-child work hours (earnings)
- ▶ Comparison to existing approaches
  - ▶ IV-IVF might overstate penalty in the short run
  - ▶ ES might overstate penalty in both short and medium run

# Appendix

Literature

Identification Math

Treatment Success

Balance

Type Shares

Trimming Shares

Monotonicity

Bound Width

Extensions

Application to Other Settings

References



## Related Literature

Gender inequality in labor market outcomes.

- ▶ Bertrand (2011); Blau & Kahn (2017) for review.

# Related Literature

Gender inequality in labor market outcomes.

- ▶ Bertrand (2011); Blau & Kahn (2017) for review.
- ▶ Role of parenthood with selection and (partially) dynamic effects:
  - ▶ Bensnes et al. (2023); Gallen et al. (2023) [Discussion](#)
  - ▶ Static by time since birth and homogeneous across individuals.

## Related Literature

Gender inequality in labor market outcomes.

- ▶ Bertrand (2011); Blau & Kahn (2017) for review.
- ▶ Role of parenthood with selection and (partially) dynamic effects:
  - ▶ Bensnes et al. (2023); Gallen et al. (2023) [Discussion](#)
  - ▶ Static by time since birth and homogeneous across individuals.

**No paper to date addresses endogenous timing and dynamic (and heterogeneous) effects.**

# Related Literature

Gender inequality in labor market outcomes.

- ▶ Bertrand (2011); Blau & Kahn (2017) for review.
- ▶ Role of parenthood with selection and (partially) dynamic effects:
  - ▶ Bensnes et al. (2023); Gallen et al. (2023) [Discussion](#)
  - ▶ Static by time since birth and homogeneous across individuals.

**No paper to date addresses endogenous timing and dynamic (and heterogeneous) effects.**

Main methodological ideas closely related to:

- ▶ Van den Berg & Vikström (2022): sequential treatment assignment.
- ▶ Lee (2005); Zhang & Rubin (2003): bounds with missing data.

[Back](#) [Literature](#)

Main idea:

1. Estimate effect in first period after treatment (while there are no later-mothers)
2. For individuals who are treated in second period, plug in estimate from the first
3. Repeat for all periods . . .

Required (intuitive) assumptions:

1. Effect must be similar between women who do and who do not enter motherhood later
2. Effect cannot vary over the life-cycle

[Back](#)

## Literature (cont.)

Parenthood, labor market outcomes, and gender equality:

- ▶ Event studies: Angelov et al. (2016); Chung et al. (2017); Kleven, Landais, Posch, et al. (2019); Eichmeyer & Kent (2022),
- ▶ Abortion access: A. R. Miller (2011); Brooks & Zohar (2021)
- ▶ Infertility: Agüero & Marks (2008); Cristia (2008)
- ▶ Sibling sex mix: Angrist & Evans (1996); Iacovou (2001); Cruces & Galiani (2007); Maurin & Moschion (2009); Hirvonen (2009)
- ▶ Twins: Rosenzweig & Wolpin (1980); Bronars & Grogger (1994); Jacobsen et al. (1999); Vere (2011)
- ▶ Miscarriages: Hotz et al. (2005)

Methodological paper on dynamic compliance and treatment effects:

- ▶ Heckman et al. (2016); Han (2021); Van den Berg & Vikström (2022)

[Back](#)

# Naive Comparison: IV vs ES

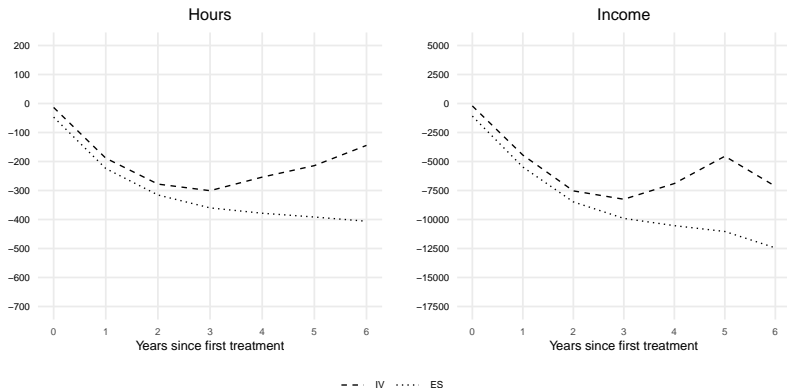


Figure 5: Comparison of IV and ES estimators using main sample

[Back](#)

# What are the counterfactuals?



# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ Want/plan children

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ Get with medical assistance

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

Childless outcome:

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

Childless outcome:

- ▶ Do not try
- ▶ Try and fail naturally
- ▶ Try and fail with medical assistance (+ naturally?)



# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

Childless outcome:

- ▶ Do not try
- ▶ Try and fail naturally
- ▶ **Try and fail with medical assistance (+ naturally?)**

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

Childless outcome:

- ▶ Do not try
- ▶ Try and fail naturally
- ▶ **Try and fail with medical assistance (+ naturally?)**

# What are the counterfactuals?

Broadly:

- ▶ Do not want/plan children
- ▶ **Want/plan children**

Motherhood outcome:

- ▶ Get immediately
- ▶ Get naturally after few attempts
- ▶ **Get with medical assistance**

Childless outcome:

- ▶ Do not try
- ▶ Try and fail naturally
- ▶ **Try and fail with medical assistance (+ naturally?)**

Extrapolation requires carefully addressing mental health consequences of failure (and medical procedures)

[Back](#)

## Identification Intuition (cont.)

## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|N=0],$$

## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|N=0],$$

with:

$$w(P) \propto \frac{1}{\prod_{g=1}^P \Pr(D_g = 0|P \geq g)} \stackrel{\text{if } \Pr \text{ const.}}{=} \frac{1}{\alpha^P}.$$

## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|N=0],$$

with:

$$w(P) \propto \frac{1}{\prod_{g=1}^P \Pr(D_g = 0|P \geq g)} \stackrel{\text{if } \Pr \text{ const.}}{=} \frac{1}{\alpha^P}.$$

Step 2:

$$\mathbb{E}[N] = \mathbb{E}[w(P)C|\text{no success}],$$



## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|N=0],$$

with:

$$w(P) \propto \frac{1}{\prod_{g=1}^P \Pr(D_g = 0|P \geq g)} \stackrel{\text{if Pr const.}}{=} \frac{1}{\alpha^P}.$$

Step 2:

$$\mathbb{E}[N] = \mathbb{E}[w(P)C|\text{no success}],$$

Step 3:

1.  $Y$ 's among  $D_1 = 1$  “reveal” the distribution of  $Y(1)$ 's
2. Assume women with  $N = 0$  are in the left/right tail
3. Bounds on  $\mathbb{E}[Y(1)|N=0]$

## Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0, P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, N=0, G=j] \\ &= \mathbb{E}[Y(0)|N=0, G=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|N=0],$$

with:

$$w(P) \propto \frac{1}{\prod_{g=1}^P \Pr(D_g = 0|P \geq g)} \stackrel{\text{if Pr const.}}{=} \frac{1}{\alpha^P}.$$

Step 2:

$$\mathbb{E}[N] = \mathbb{E}[w(P)C|\text{no success}],$$

Step 3:

1.  $Y$ 's among  $D_1 = 1$  “reveal” the distribution of  $Y(1)$ 's
2. Assume women with  $N = 0$  are in the left/right tail
3. Bounds on  $\mathbb{E}[Y(1)|N=0]$

# Estimator Intuition: Math with Coins

- ▶ Each individuals flips a coin once
- ▶ Some may chose to flip again if heads come up
- ▶ Number of flips ( $P$ ) observed
- ▶  $Y$  only revealed for those who never flip heads

$$\mathbb{E}[Y] = \mathbb{E}\left[\frac{1}{(1/2)^P} Y \mathbf{1}_{\{\text{no heads}\}}\right]$$

Back

# Formal Identification

$$\Delta_L = \mu_L - \mu_C$$

$$\Delta_U = \mu_U - \mu_C$$

$$\mu_C = \mathbb{E} \left[ \frac{Y}{\prod_j^P (1 - p_j(X_j))} \middle| \mathbf{1}_{Child} = 0 \right] \mathbb{E} \left[ \prod_j^P (1 - p_j(X_j)) \middle| \mathbf{1}_{Child} = 0 \right]$$

$$\mu_L = \mathbb{E} \left[ \frac{Y}{p_1(X_1)} \middle| D_1 = 1, Y < y(1 - s) \right] \mathbb{E} [p_1(X_1) | D_1 = 1, Y < y(1 - s)]$$

$$\mu_U = \mathbb{E} \left[ \frac{Y}{p_1(X_1)} \middle| D_1 = 1, Y > y(s) \right] \mathbb{E} [p_1(X_1) | D_1 = 1, Y > y(s)]$$

$$y(q) = G^{-1}(q)$$

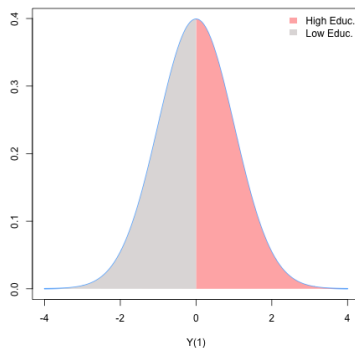
$$G(q) = \mathbb{E} \left[ \frac{\mathbf{1}(Y \leq q)}{p_1(X_1)} \middle| D_1 = 1 \right] \mathbb{E} [p_1(X_1) | D_1 = 1]$$

$$s = \mathbb{E} \left[ \frac{\mathbf{1}_{Child}}{\prod_j^P (1 - p_j(X_j))} \middle| W = 0 \right] \mathbb{E} \left[ \prod_j^P (1 - p_j(X_j)) \middle| W = 0 \right],$$

where  $W = 1 - \prod_{j=1}^P (1 - D_j)$ .

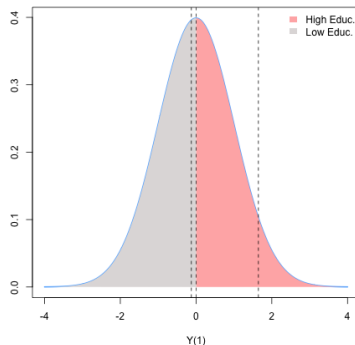
# Tightening Bounds with Covariates

1. Separate distribution of motherhood outcomes into low and high education groups



# Tightening Bounds with Covariates (cont.)

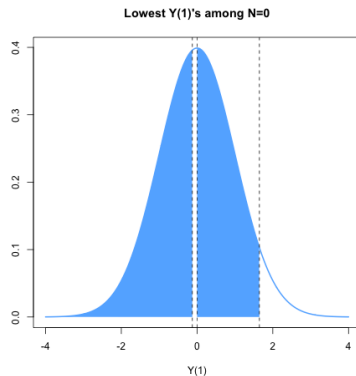
2. Estimate  $\Pr(N = 0|high) = 0.9$  and  $\Pr(N = 0|low) = 0.9$  on control group
3. Assume most extreme distribution of types within educ. groups



# Tightening Bounds with Covariates (cont.)

4. The mean of the trimmed distribution gives new lower bound

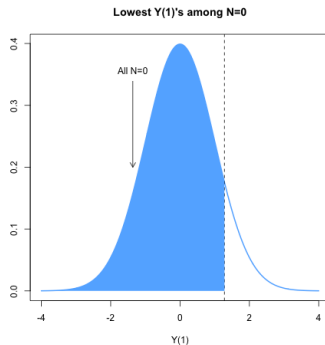
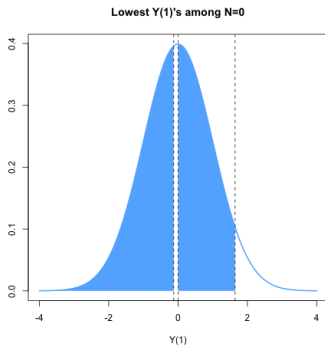
$$\mathbb{E}_{educ}[LB_{\mathbb{E}[Y(1)|N=0]}(educ)] \leq \mathbb{E}[Y(1)|N=0]$$



# Comparing the Bounds

Conditional lower bounds is higher than unconditional:

$$\mathbb{E}_{educ}[LB_{\mathbb{E}[Y(1)|N=0]}(educ)] \geq LB_{\mathbb{E}[Y(1)|N=0]}$$

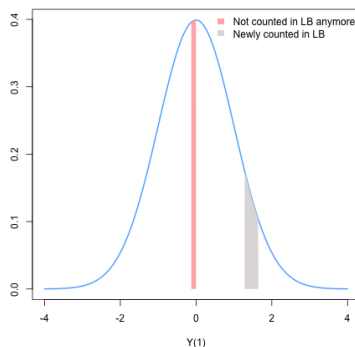




# Comparing the Bounds (cont.)

Conditional lower bounds is higher than unconditional:

$$\mathbb{E}_{educ}[LB_{\mathbb{E}[Y(1)|N=0]}(educ)] \geq LB_{\mathbb{E}[Y(1)|N=0]}$$



## Estimation

$$m_L(data, \eta_0) = \frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}} - \prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} S Y$$

## Estimation

$$m_L(data, \eta_0) = \frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}} - \prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} S Y$$

$$\eta_0 = \{s_0(x), q_1(u, x), e_j(x)\}$$

$$s_0(x) = Pr(N = 0 | X_1 = x)$$

$$q_1(u, x) = F_{Y(1)|X_1=x}^{-1}(u)$$

$$e_j(x) = Pr(D_j = 1 | P \geq j, X_j = x)$$

$$S = 1_{\{childless\}}$$

# Estimation

$$m_L(data, \eta_0) = \underbrace{\frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}}}_{\text{1st success mean below trim thresh.}} - \underbrace{\prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} S Y}_{\text{childless mean}}$$

$$\eta_0 = \{s_0(x), q_1(u, x), e_j(x)\}$$

$$s_0(x) = Pr(N = 0 | X_1 = x)$$

$$q_1(u, x) = F_{Y(1)|X_1=x}^{-1}(u)$$

$$e_j(x) = Pr(D_j = 1 | P \geq j, X_j = x)$$

$$S = 1_{\{\text{childless}\}}$$

# Estimation

$$m_L(data, \eta_0) = \underbrace{\frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}}}_{\text{1st success mean below trim thresh.}} - \underbrace{\prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} S Y}_{\text{childless mean}}$$

$$\eta_0 = \{s_0(x), q_1(u, x), e_j(x)\}$$

$$s_0(x) = Pr(N = 0 | X_1 = x)$$

$$q_1(u, x) = F_{Y(1)|X_1=x}^{-1}(u)$$

$$e_j(x) = Pr(D_j = 1 | P \geq j, X_j = x)$$

$$S = 1_{\{\text{childless}\}}$$

$$\mathbb{E}[m_L(data, \eta_0)] = \mathbb{E}[LB_{\tau_c}] \alpha_{\text{scaling}}$$

# Estimation

$$m_L(data, \eta_0) = \underbrace{\frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}}}_{\text{1st success mean below trim thresh.}} - \underbrace{\prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} S Y}_{\text{childless mean}}$$

$$\eta_0 = \{s_0(x), q_1(u, x), e_j(x)\}$$

$$s_0(x) = Pr(N = 0 | X_1 = x)$$

$$q_1(u, x) = F_{Y(1)|X_1=x}^{-1}(u)$$

$$e_j(x) = Pr(D_j = 1 | P \geq j, X_j = x)$$

$$S = 1_{\{\text{childless}\}}$$

$$\mathbb{E}[m_L(data, \eta_0)] = \mathbb{E}[LB_{\tau_c}] \alpha_{scaling}$$

$$\frac{1}{\sqrt{n}} \sum_i (m_L(data_i, \hat{\eta}) - \mathbb{E}[m_L(data_i, \eta_0)]) \xrightarrow{d} ?$$

# Inference

- ▶ Semenova (2020) develops DML estimator for Lee bounds
- ▶ When  $G = 1$ , Lee bounds = my approach
- ▶ I extend estimator in Semenova (2020) to allow  $G \geq 1$

# Inference

- ▶ Semenova (2020) develops DML estimator for Lee bounds
- ▶ When  $G = 1$ , Lee bounds = my approach
- ▶ I extend estimator in Semenova (2020) to allow  $G \geq 1$

$$g_L(data, \eta_0) = m_L(W, \eta_0) + corr_L(data, \eta_0)$$



# Inference

- ▶ Semenova (2020) develops DML estimator for Lee bounds
- ▶ When  $G = 1$ , Lee bounds = my approach
- ▶ I extend estimator in Semenova (2020) to allow  $G \geq 1$

$$g_L(data, \eta_0) = m_L(W, \eta_0) + corr_L(data, \eta_0)$$

$$\mathbb{E}[corr_L(data, \eta_0)] = 0$$

$$\left. \frac{\partial \mathbb{E}[g_L(data, \eta)]}{\partial \eta} \right|_{\eta_0} = 0$$

# Inference

- ▶ Semenova (2020) develops DML estimator for Lee bounds
- ▶ When  $G = 1$ , Lee bounds = my approach
- ▶ I extend estimator in Semenova (2020) to allow  $G \geq 1$

$$g_L(data, \eta_0) = m_L(W, \eta_0) + corr_L(data, \eta_0)$$

$$\mathbb{E}[corr_L(data, \eta_0)] = 0$$

$$\left. \frac{\partial \mathbb{E}[g_L(data, \eta)]}{\partial \eta} \right|_{\eta_0} = 0$$

$$\frac{1}{\sqrt{n}} \sum_i g_L(data_i, \widehat{\eta_{CF_i}}) \xrightarrow{p} \frac{1}{\sqrt{n}} \sum_i g_L(data_i, \eta_0) \quad (*)$$

# Inference

- ▶ Semenova (2020) develops DML estimator for Lee bounds
- ▶ When  $G = 1$ , Lee bounds = my approach
- ▶ I extend estimator in Semenova (2020) to allow  $G \geq 1$

$$g_L(data, \eta_0) = m_L(W, \eta_0) + corr_L(data, \eta_0)$$

$$\mathbb{E}[corr_L(data, \eta_0)] = 0$$

$$\left. \frac{\partial \mathbb{E}[g_L(data, \eta)]}{\partial \eta} \right|_{\eta_0} = 0$$

$$\frac{1}{\sqrt{n}} \sum_i g_L(data_i, \widehat{\eta_{CF_i}}) \xrightarrow{p} \frac{1}{\sqrt{n}} \sum_i g_L(data_i, \eta_0) \quad (*)$$

$$\frac{1}{\sqrt{n}} \sum_i (g_L(data_i, \eta_0) - \mathbb{E}[m_L(data_i, \eta_0)]) \xrightarrow{d} N(0, \sigma^2)$$

# Narrowing the Bounds with Covariates (cont.)

Alternative extension of Lee bounds (to my knowledge)

- ▶ Take some function  $g(x)$
- ▶  $\mathbb{E}[g(X_1)|N=0]$  can be identified on women who remain childless
- ▶ Take  $\mathbb{E}[Y(1)|N=0] = \mathbb{E}[g(X_1) + \varepsilon|N=0]$
- ▶ Only need to bound  $\mathbb{E}[\varepsilon|N=0]$
- ▶  $g(X_1)$  can be directly chosen to minimize the spread in residuals, e.g. OLS of  $Y$  on  $X_1$  for women with  $D_1 = 1$ .
- ▶ Since residuals typically have a narrower distribution, this gives narrower bounds.
- ▶ Also, likely to improve asymptotic efficiency: only need to compare residuals in both groups,  $\mathbb{E}[g(X_1)|N=0]$  is the same for treated and control.

[Back \(DML\)](#)

[Back \(extensions\)](#)

# Randomness in IUI and IVF

Treatment success is not completely random.

# Randomness in IUI and IVF

Treatment success is not completely random.

- ▶ Arguably the most important factor for success also related to labor market outcomes is the age of the woman and their partner.

# Randomness in IUI and IVF

Treatment success is not completely random.

- ▶ Arguably the most important factor for success also related to labor market outcomes is the age of the woman and their partner.
- ▶ I allow the probability of success at each attempt to depend on the age of the woman and their partner at the time of the attempt interacted with treatment type.

# Randomness in IUI and IVF

Treatment success is not completely random.

- ▶ Arguably the most important factor for success also related to labor market outcomes is the age of the woman and their partner.
- ▶ I allow the probability of success at each attempt to depend on the age of the woman and their partner at the time of the attempt interacted with treatment type.

Other (medical) factors relevant for IVF success appear to be largely unrelated to labor market outcomes (Lundborg et al., 2017).

[Back](#)



# Treatment Success

- ▶ I impute treatment success as having a child born within 10 months after treatment without subsequent treatments in between.
  - ▶ Validated to reflect medical records of treatment success (Lundborg et al., 2017).

[Back](#)

**Table 1:** First treatment outcomes and descriptives

	Success (1)	Fail (2)	Difference (1)-(2)	Dif. cond. age FE (1)-(2) cond. age
Work (W)	0.881 [0.324]	0.863 [0.344]	0.018 (0.009)	0.008 (0.009)
Work (P)	0.884 [0.320]	0.865 [0.341]	0.019 (0.009)	0.014 (0.009)
Hours (W)	1239.696 [605.070]	1208.255 [634.840]	31.441 (16.168)	17.578 (15.812)
Hours (P)	1473.383 [658.917]	1438.880 [695.345]	34.502 (17.699)	22.690 (17.587)
Income 1000s € (W)	28.049 [19.559]	27.434 [20.232]	0.615 (0.516)	0.942 (0.496)
Income 1000s € (P)	37.173 [26.484]	36.959 [29.443]	0.214 (0.746)	0.896 (0.732)
Bachelor deg. (W)	0.608 [0.488]	0.605 [0.489]	0.002 (0.013)	0.018 (0.012)
Bachelor deg. (P)	0.593 [0.491]	0.598 [0.490]	-0.004 (0.013)	0.008 (0.012)
Age (W)	31.643 [4.016]	32.384 [4.383]	-0.741 (0.111)	
Age (P)	34.672 [5.527]	35.459 [5.993]	-0.787 (0.152)	
Observations	1,716	13,788		
Joint <i>p</i> -val.			0.000	0.536

*Note:* Labor market outcomes measured year before first treatment. (W) - woman, (P) - partner. Standard deviations in brackets. Standard errors in parentheses.

# Balance in Later Treatments

Table 2: Balance in later treatments

	D2	D3	D4	D5	D6	D7	D8	D9	D10
Work (W)	0.013 (0.009)	-0.002 (0.010)	0.023 (0.011)	0.008 (0.012)	0.030 (0.013)	0.007 (0.014)	-0.008 (0.017)	0.016 (0.019)	0.041 (0.026)
Work (P)	0.011 (0.010)	0.014 (0.010)	0.005 (0.011)	0.014 (0.012)	-0.004 (0.013)	-0.008 (0.014)	0.001 (0.017)	0.016 (0.020)	0.040 (0.027)
Hours (W)	37.050 (17.373)	-0.615 (18.648)	45.477 (20.127)	39.327 (21.930)	68.596 (24.489)	25.780 (26.043)	-5.734 (31.176)	81.149 (36.869)	29.860 (49.101)
Hours (P)	29.074 (19.336)	28.347 (20.807)	18.441 (22.614)	35.597 (24.685)	-7.332 (27.215)	-15.344 (28.618)	0.360 (34.381)	47.511 (41.158)	49.279 (55.440)
Income 1000s € (W)	1.786 (0.548)	0.283 (0.592)	1.123 (0.647)	1.672 (0.710)	1.380 (0.786)	0.489 (0.831)	0.417 (1.030)	1.839 (1.240)	-0.297 (1.714)
Income 1000s € (P)	0.221 (0.820)	1.277 (0.846)	1.588 (0.923)	1.125 (1.018)	-0.542 (1.123)	-0.370 (1.212)	1.567 (1.423)	1.001 (1.666)	-0.202 (2.277)
Bachelor deg. (W)	0.002 (0.013)	0.026 (0.014)	-0.020 (0.015)	0.001 (0.017)	-0.003 (0.019)	0.003 (0.020)	0.023 (0.024)	-0.012 (0.028)	0.045 (0.038)
Bachelor deg. (P)	0.005 (0.013)	0.010 (0.014)	0.011 (0.016)	0.007 (0.017)	-0.003 (0.019)	0.013 (0.020)	0.020 (0.024)	0.012 (0.029)	-0.014 (0.039)
Age (W)	0.001 (0.011)	-0.007 (0.015)	-0.040 (0.019)	0.024 (0.023)	0.013 (0.026)	-0.001 (0.028)	-0.046 (0.036)	-0.027 (0.043)	-0.017 (0.059)
Age (P)	0.001 (0.011)	-0.007 (0.015)	-0.040 (0.019)	0.024 (0.023)	0.013 (0.026)	-0.001 (0.028)	-0.046 (0.036)	-0.027 (0.043)	-0.017 (0.059)
Observations	12,955	10,759	8,714	6,969	5,403	3,938	2,718	1,848	1,173
Joint <i>p</i> -val.	0.071	0.737	0.057	0.439	0.420	0.991	0.836	0.508	0.437

Note: Each column describes the differences between those treated successfully and those treated unsuccessfully at the respective treatment attempt conditional on fixed effects for age-at-treatment interacted with fixed effects for treatment type. Labor market outcomes and age measured year before first treatment. (W) - woman, (P) - partner. Standard errors in parentheses.

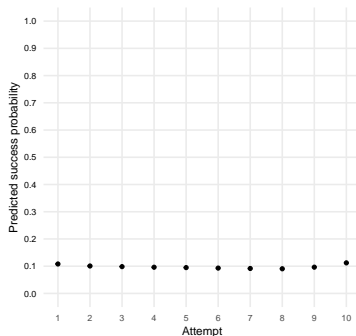
# Representative and Relevant Treatment group

Table 3: Full sample, relevant sample, and representative sample

	Success (1)	Fail (2)	Relevant (3)	Representative (4)	Success vs rep. (1)-(4)	Rel. vs rep. (3)-(4)
Work (W)	0.881 [0.324]	0.863 [0.344]	0.822 [0.334]	0.801 [0.399]	0.080 (0.010)	0.021 (0.005)
Work (P)	0.884 [0.320]	0.865 [0.341]	0.850 [0.344]	0.783 [0.412]	0.101 (0.010)	0.066 (0.005)
Hours (W)	1239.696 [605.070]	1208.255 [634.840]	1120.310 [583.894]	1071.721 [697.609]	167.975 (16.879)	48.589 (8.254)
Hours (P)	1473.383 [658.917]	1438.880 [695.345]	1392.628 [663.323]	1245.385 [793.411]	227.998 (19.197)	147.243 (9.376)
Income 1000s € (W)	28.049 [19.559]	27.434 [20.232]	24.925 [15.086]	20.903 [17.981]	7.146 (0.435)	4.021 (0.213)
Income 1000s € (P)	37.173 [26.484]	36.959 [29.443]	35.002 [23.998]	27.544 [28.685]	9.630 (0.694)	7.459 (0.339)
Bachelor deg. (W)	0.608 [0.488]	0.605 [0.489]	0.591 [0.414]	0.576 [0.494]	0.032 (0.012)	0.015 (0.006)
Bachelor deg. (P)	0.593 [0.491]	0.598 [0.490]	0.582 [0.416]	0.554 [0.497]	0.040 (0.012)	0.029 (0.006)
Age (W)	31.643 [4.016]	32.384 [4.383]	33.284 [3.892]	28.384 [4.648]	3.259 (0.112)	4.900 (0.055)
Age (P)	34.672 [5.527]	35.459 [5.993]	36.327 [3.924]	28.384 [4.655]	6.288 (0.113)	7.943 (0.055)
Observations	1,716	13,788	5,103	374,812		

Note: Labor market outcomes measured year before first treatment for main sample and year and 9 months before birth of first child for representative sample. Representative sample selected to match main sample by year of conception. Relevant sample consists of women in the main sample who remain childless weighted to account for differences in the probability to remain childless. (W) - woman, (P) - partner. Standard deviations in brackets. Standard errors in parentheses.

# Predicted Success Prob. per Treatment



**Figure 6:** Predicted success probability holding  $X$  fixed at first attempt average

[Back](#)

# Attempts

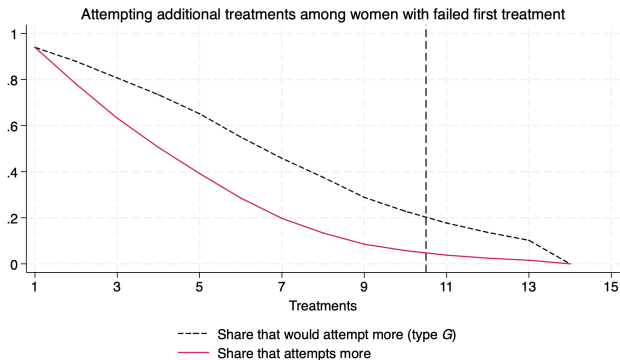


Figure 7: Number of treatments and type

[Back](#)

# Non-treatment Conception by Type

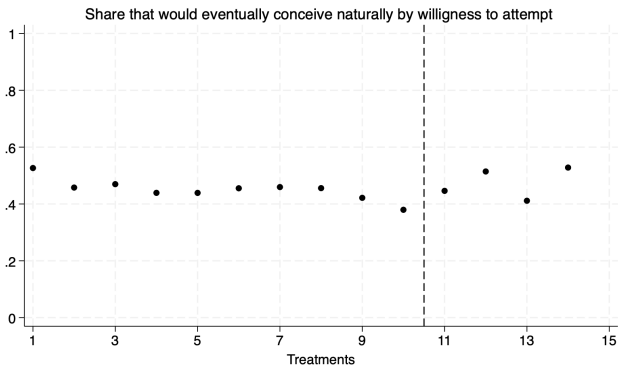


Figure 8: Conceiving naturally and willingness to attempt

[Back](#)

# Trimming shares

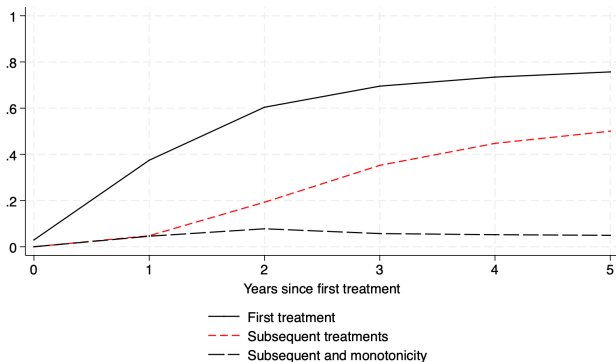


Figure 9: Trimming share under different information

[Back](#)



# Correction Term

$$\begin{aligned} \text{corr}_L(\text{data}, \eta_0) &= q_1(s_0(X_1), X_1) \prod_{j=1}^P \frac{1 - D_j}{1 - e_j(X_j)} (S - s(0, X_1)) \\ &\quad - q_1(s_0(X_1), X_1) \frac{D_1}{e_1(X_1)} (1_{\{Y < q_1(s_0(X_1), X_1)\}} - s_0(X_1)) \\ &\quad - \frac{D_1 - e_1(X_1)}{e_1(X_1)} z_L^+(1, X_1) s(0, X_1) \\ &\quad + \sum_k \mathbb{1}_{P \geq j} \prod_j^{k-1} \frac{1 - D_j}{1 - e_j(X_j)} \frac{e_k(X_k) - D_k}{1 - e_k(X_k)} (s_k(0, X_k) \beta_k(0, X_k)) \\ &\quad + \sum_k \mathbb{1}_{P \geq j} \prod_j^{k-1} \frac{1 - D_j}{1 - e_j(X_j)} \frac{e_k(X_k) - D_k}{1 - e_k(X_k)} q_1(s_0(X_1), X_1) (s(0, X_1) - s_k(0, X_k)) \end{aligned}$$

Back

# Bounds: Absolute

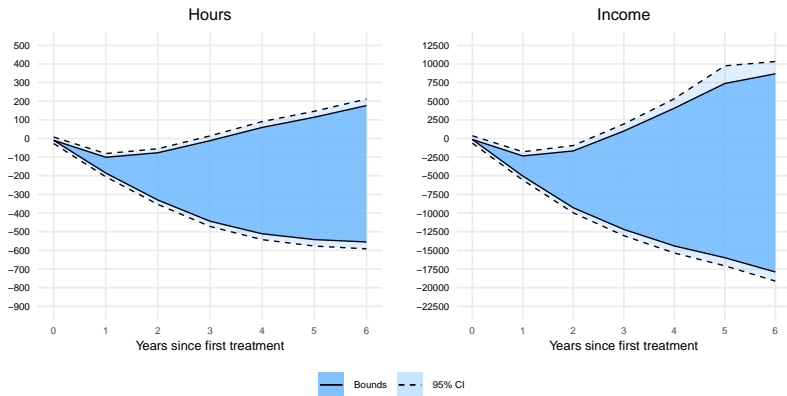


Figure 10: Bounds effects

[Back](#)

# Bounds: Hours - Comparison to Baseline Lee Bounds

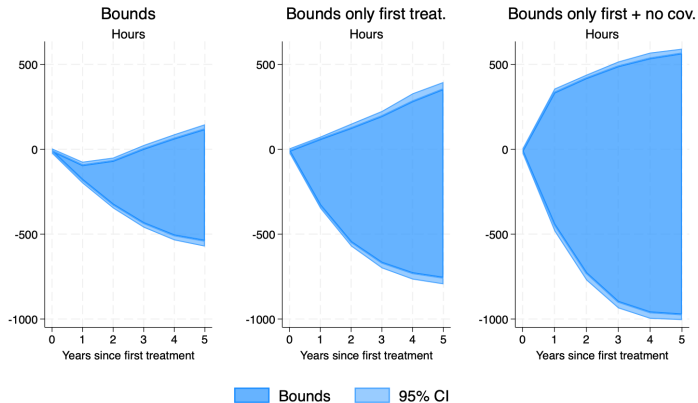


Figure 11: Comparison with baseline Lee: hours

# Bounds: Income - Comparison to Baseline Lee Bounds

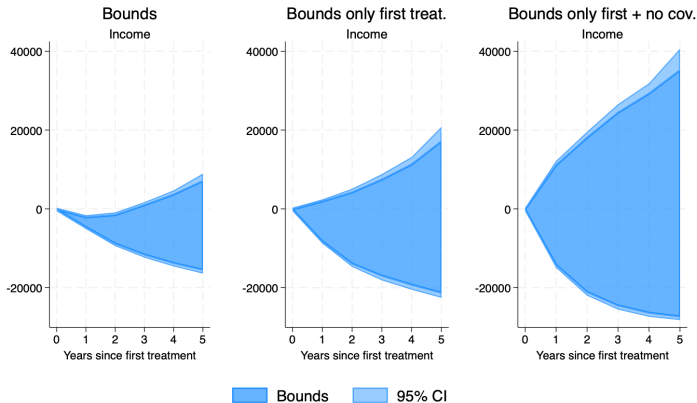


Figure 12: Comparison with baseline Lee: income

## Monotonicity (cont.)

Is monotonicity realistic?

## Monotonicity (cont.)

Is monotonicity realistic?

- ▶ Yes, if families are determined to have at least one child.
  - ▶ Decreasing marginal returns to children.
  - ▶ Stronger sufficient assumption: success cannot increase total (natural) births.

# Monotonicity (cont.)

Is monotonicity realistic?

- ▶ Yes, if families are determined to have at least one child.
  - ▶ Decreasing marginal returns to children.
  - ▶ Stronger sufficient assumption: success cannot increase total (natural) births.
- ▶ No, if first treatment success increases the likelihood of attempting to conceive naturally.

# Monotonicity (cont.)

Is monotonicity realistic?

- ▶ Yes, if families are determined to have at least one child.
  - ▶ Decreasing marginal returns to children.
  - ▶ Stronger sufficient assumption: success cannot increase total (natural) births.
- ▶ No, if first treatment success increases the likelihood of attempting to conceive naturally.
  - ▶ Couples may realize they are fertile and try more.



# Monotonicity (cont.)

Is monotonicity realistic?

- ▶ Yes, if families are determined to have at least one child.
  - ▶ Decreasing marginal returns to children.
  - ▶ Stronger sufficient assumption: success cannot increase total (natural) births.
- ▶ No, if first treatment success increases the likelihood of attempting to conceive naturally.
  - ▶ Couples may realize they are fertile and try more.
  - ▶ First child may “save the relationship” resulting in more attempts to conceive.

# Monotonicity (cont.)

Is monotonicity realistic?

- ▶ Yes, if families are determined to have at least one child.
  - ▶ Decreasing marginal returns to children.
  - ▶ Stronger sufficient assumption: success cannot increase total (natural) births.
- ▶ No, if first treatment success increases the likelihood of attempting to conceive naturally.
  - ▶ Couples may realize they are fertile and try more.
  - ▶ First child may “save the relationship” resulting in more attempts to conceive.
- ▶ Robustness: restrict to only couples that stay together

Effects

Back

Benefit of monotonicity

Graphic intuition

# Benefit of Monotonicity

- ▶ Women who conceive a second child naturally are not the women who would remain childless.

# Benefit of Monotonicity

- ▶ Women who conceive a second child naturally are not the women who would remain childless.
- ▶ This restricts which women among successfully treated could have remained childless had all treatment attempts failed.

# Benefit of Monotonicity

- ▶ Women who conceive a second child naturally are not the women who would remain childless.
- ▶ This restricts which women among successfully treated could have remained childless had all treatment attempts failed.
- ▶ Narrower bounds.

[Intuition](#)

[Back](#)

# Monotonicity: Intuition (1)

Identify distribution of motherhood outcomes from group whose first treatment succeeds:

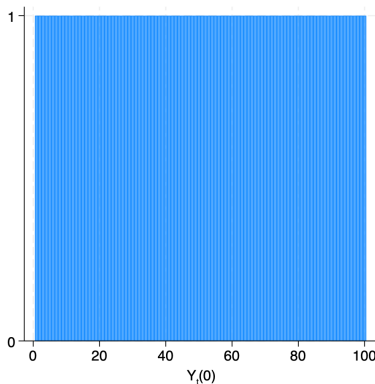


Figure 13: Distribution of potential motherhood outcomes

## Monotonicity: Intuition (2)

Without monotonicity: 20 with highest/lowest outcomes:

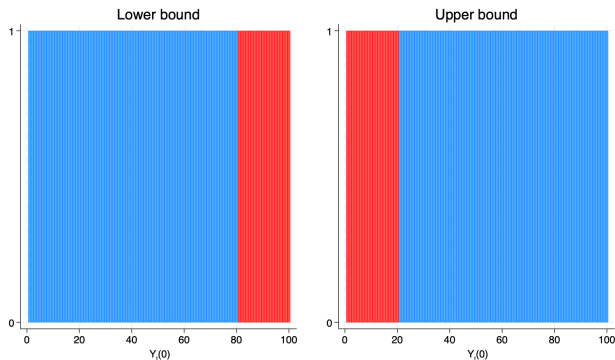


Figure 14: Distribution of potential motherhood outcomes

## Monotonicity: Intuition (3)

With monotonicity: first, drop 10 who conceive again naturally:

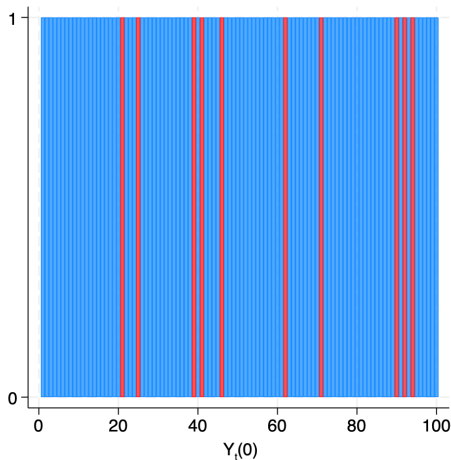


Figure 15: Distribution of potential motherhood outcomes



## Monotonicity: Intuition (4)

With monotonicity: second, drop another 10 with highest/lowest outcomes:

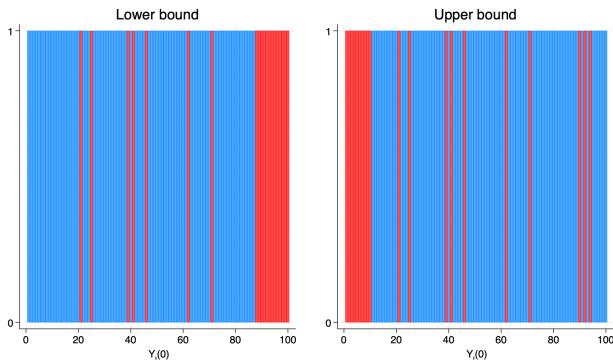


Figure 16: Distribution of potential motherhood outcomes

# Monotonicity: Intuition (5)

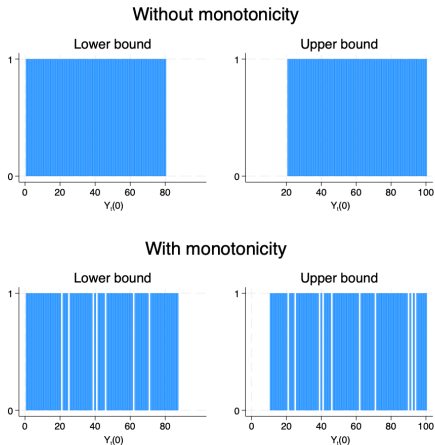


Figure 17: Distribution of potential motherhood outcomes

# Monotone Bounds: Absolute

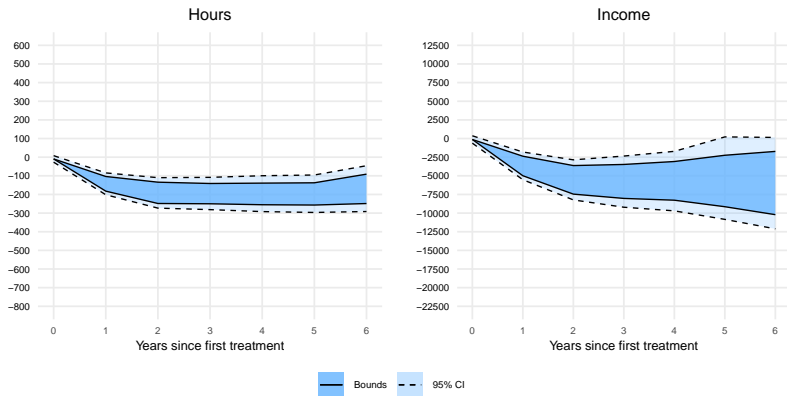


Figure 18: Monotone bounds: absolute terms

[Back](#)

# How Wide are the Bounds?

6 years after first treatment:

- ▶ Bounds:
  - ▶ 1 SD of pre-treatment hours
  - ▶ 1 SD of pre-treatment earnings
- ▶ Monotone bounds:
  - ▶ 0.15 SD of pre-treatment hours
  - ▶ 0.25 SD of pre-treatment earnings

[Back](#)

# Extensions

## Outcomes:

- ▶ Fatherhood penalty   Absolute   Percentage
- ▶ Decomposing gender inequality   Share explained by children
- ▶ Effect of delaying motherhood   Absolute   Cumulative

## Existing estimators:

- ▶ Are existing estimates biased?   IV-IVF equivalent   Placebo event   Placebo ineq.
- ▶ Are estimates less informative than existing?   Confidence intervals

## Robustness:

- ▶ Bias due to depression   Effect on depression   Bounds for non-depressed
- ▶ Correcting for parental leave   Max. leave
- ▶ Inequality correcting for age   De-aging partners
- ▶ Stable complier group   Childless final period
- ▶ Estimator without DML   Effects
- ▶ Relaxing monotonicity   Direction   Partnered only

## Other:

- ▶ Heterogeneity   Covariates   Willingness to try
- ▶ Population imputation\*   ES pop. vs IVF   Mother. imp.   Childless imp.   Effect imp.

# Monotone Bounds: Women who Remain Childless

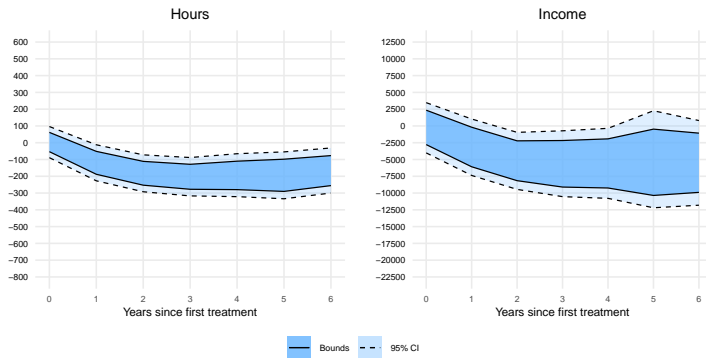


Figure 19: Monotone bounds using final status

[Back](#)

# Event Study: Population vs IUI Sample

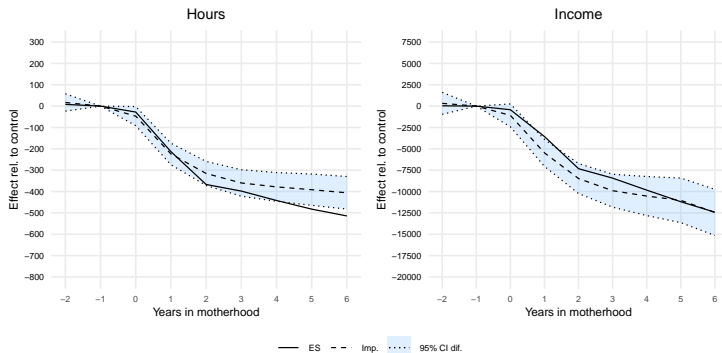


Figure 20: ES for population and women with first IUI success

[Back](#)

# Imputing Population Motherhood Outcomes Using IUI Sample

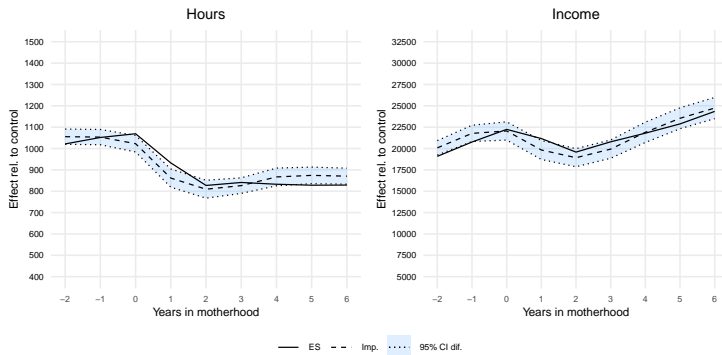


Figure 21: Population Outcomes vs IUI-imputation (age & education)

[Back](#)



# Imputing Population Childless Outcomes Using IUI Sample

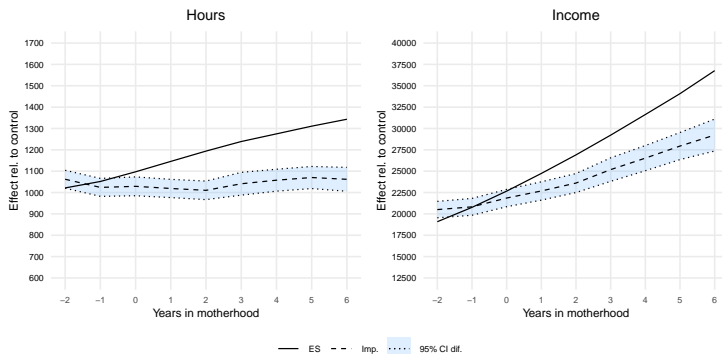


Figure 22: Population Outcomes vs IUI-imputation (age & education)

[Back](#)

# Event Study vs IUI-imputation for Population

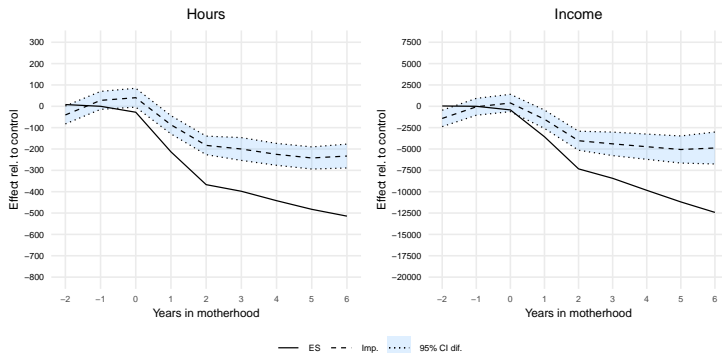
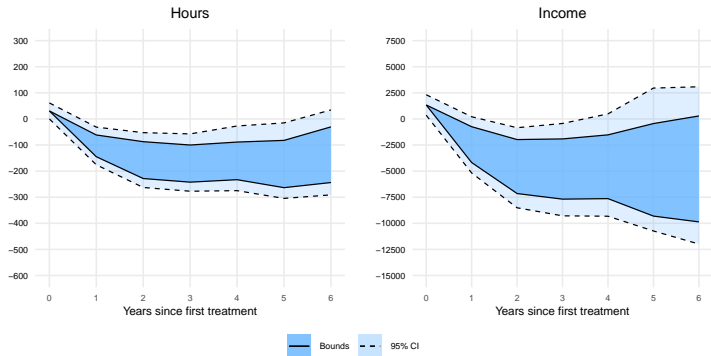


Figure 23: Event study vs IUI-imputation for population (age & education)

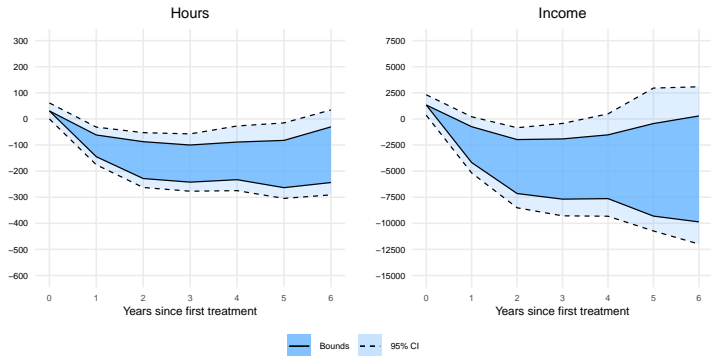
[Back](#)

# Simple estimator



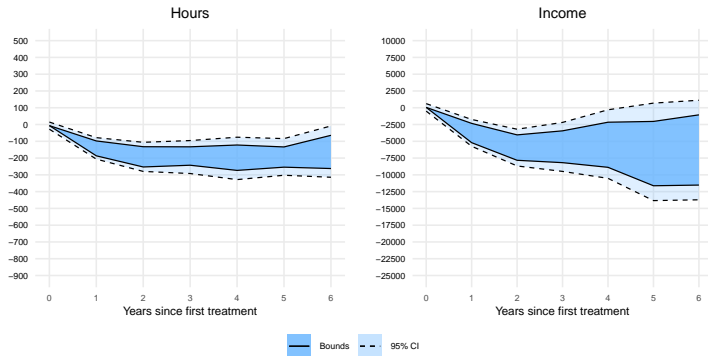
[Back](#)

# Simple estimator



[Back](#)

# Relaxing Monotonicity Direction



[Back](#)

# Heterogeneity by Covariates

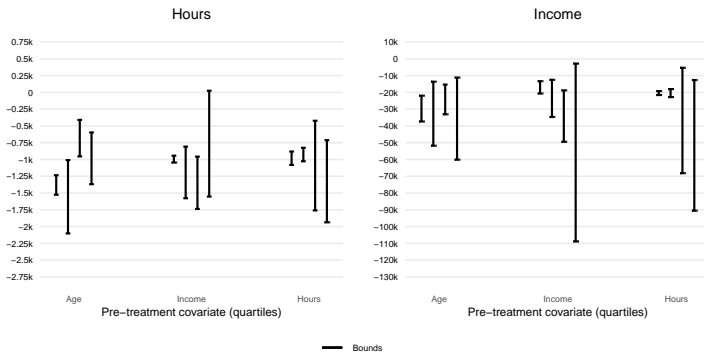


Figure 24: Cumulative outcomes after 6 years, pre-treatment covariates

[Back](#)

# Heterogeneity by Willingness to Undergo Procedures

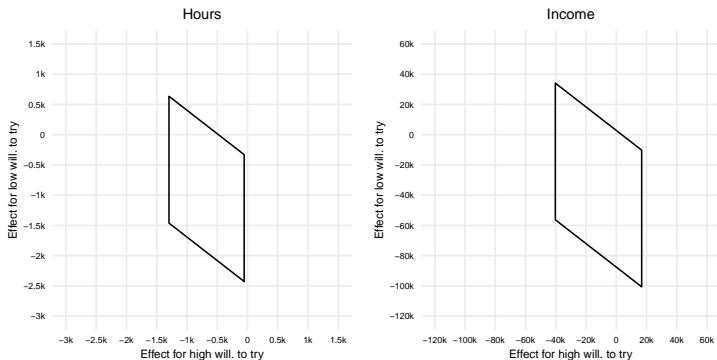


Figure 25: Cumulative outcomes 6 years after,  $G$  above or below 6

[Back](#)

# Monotone Bounds: Excluding Depression

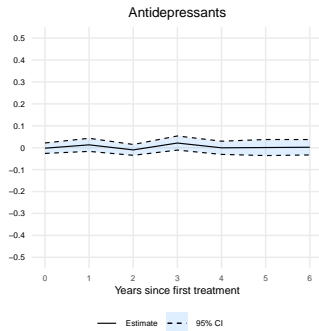


Figure 26: Sequential-IV estimates for effect on antidepressant take-up

[Back](#)



# Monotone Bounds: Excluding Depressed

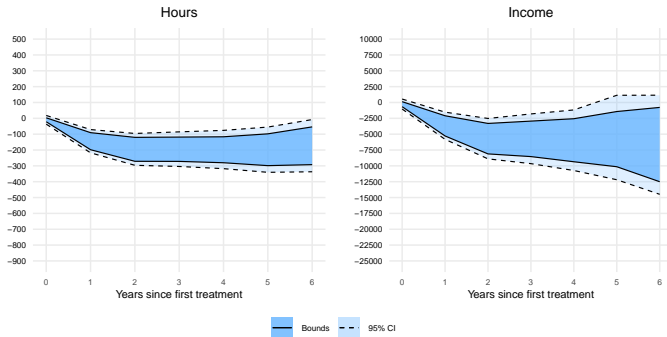


Figure 27: Monotone bounds for women who would not start antidepressants if they were to remain childless

[Back](#)

# Monotone Bounds: Assuming Maximum Leave

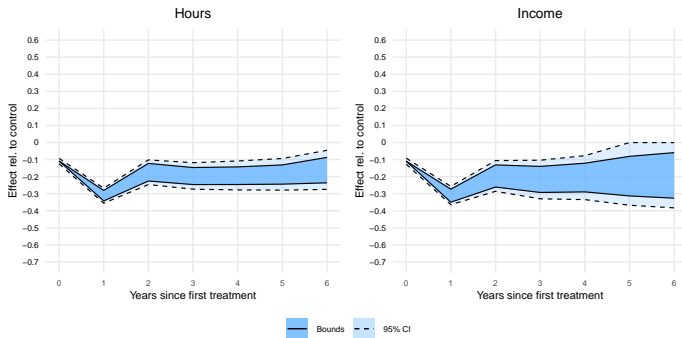


Figure 28: Monotone bounds scaling outcomes in years with childbirth by max. leave fraction

[Back](#)

# Monotone Bounds: Correcting for Partner's age

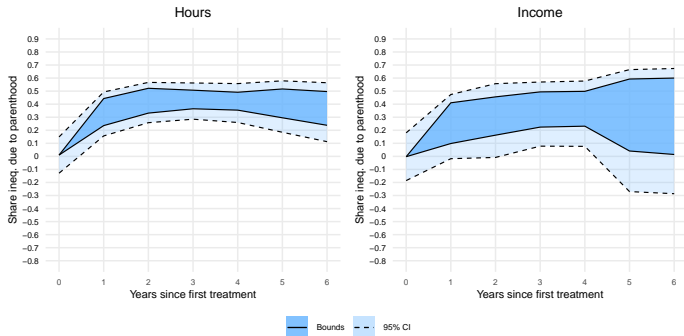


Figure 29: Monotone bounds using male income at same age as female

[Back](#)

# Monotone Bounds: Fatherhood Penalty

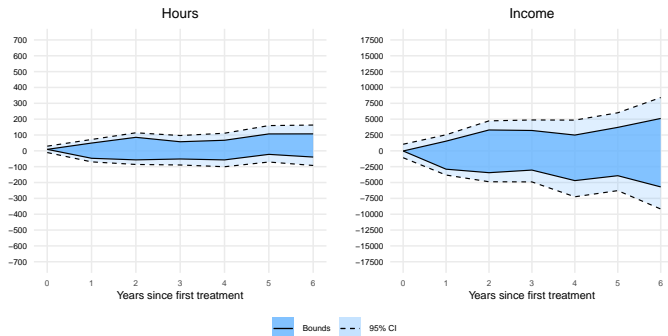


Figure 30: Monotone bounds for partners

[Back](#)

# Monotone Bounds: Fatherhood Penalty in Percent

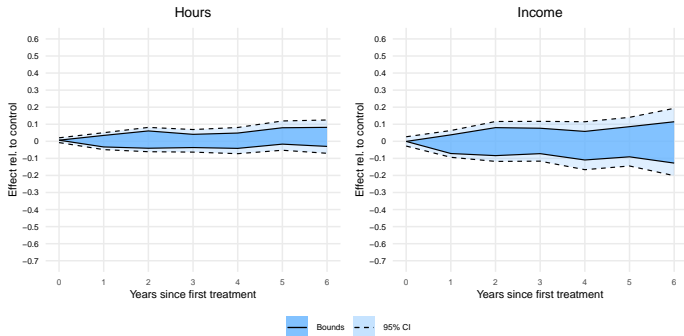


Figure 31: Monotone bounds for partners in percent

[Back](#)

# Monotone Bounds: Explaining Gender Inequality

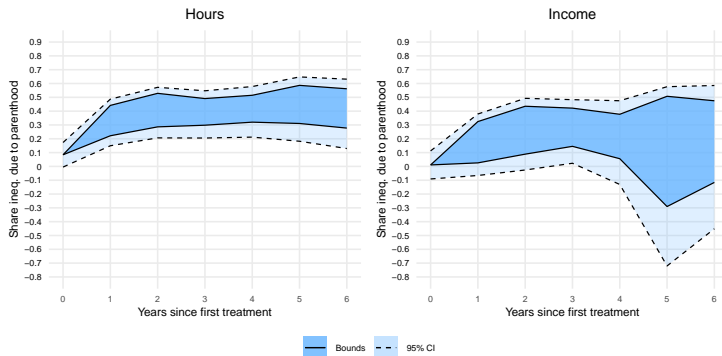


Figure 32: Share of gender inequality explained by parenthood

[Back](#)

# Are Bounds Less Informative?

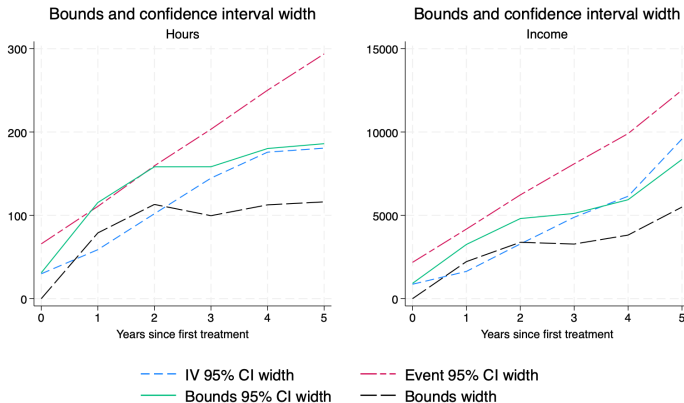


Figure 33: Confidence intervals for different methods

# Monotone Bounds and IV

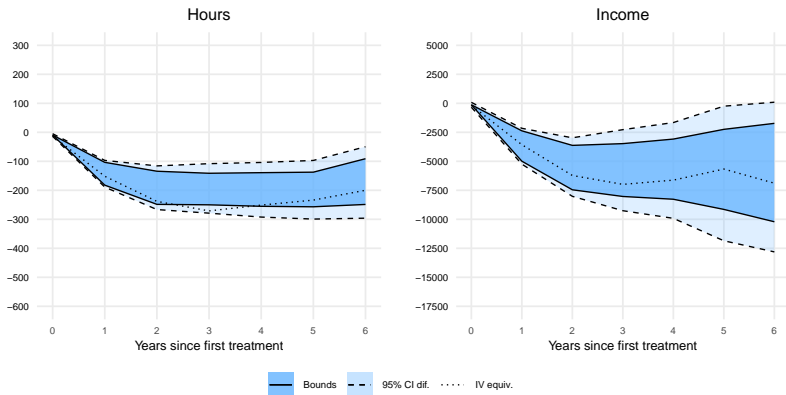


Figure 34: Bounds and IV equivalent for the same population

[Back](#)



# Placebo Event

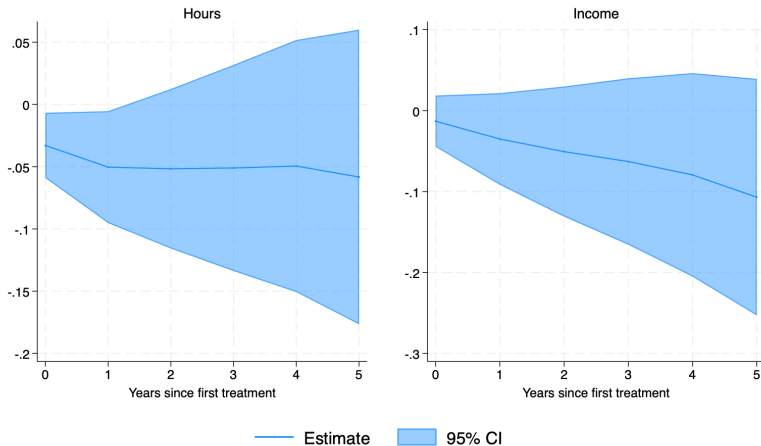


Figure 35: Placebo event study

# Inequality treating ES bias as causal

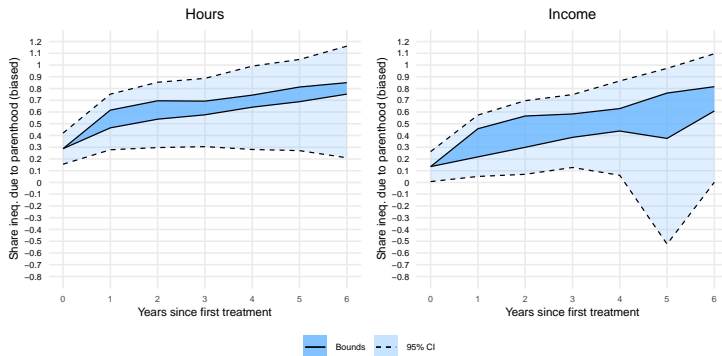


Figure 36: Placebo effects as share of bounds for the same population

Two possible interpretations:

- ▶ Event study severely overstates the penalty
- ▶ Large share of penalty is due to trying to conceive not parenthood per se

[Back](#) [Placebo as share of regular event](#)

# Yearly effect of Delaying Motherhood

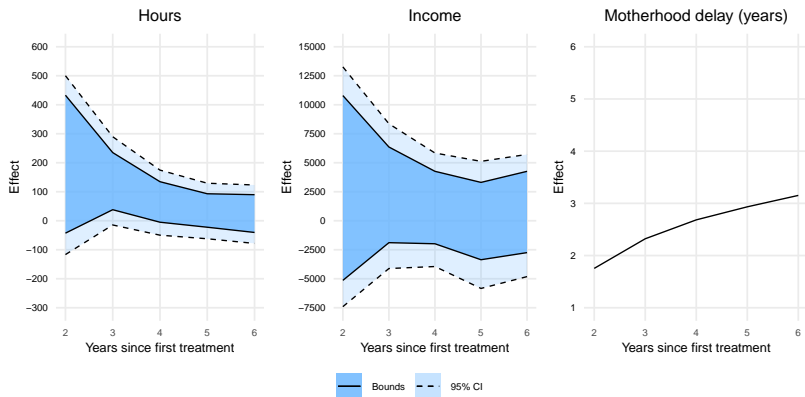


Figure 37: Effect of delaying relative to motherhood at first attempt

**Opposite of what is frequently assumed!**

[Back](#)

# Cumulative effect of Delaying Motherhood

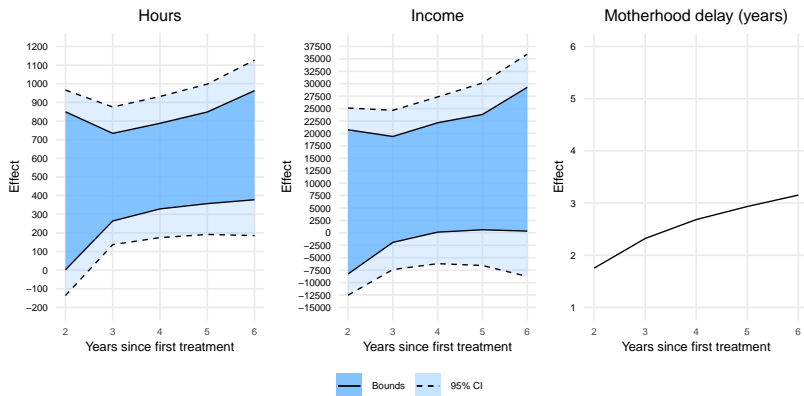


Figure 38: Effect of delaying relative to motherhood at first attempt

[Back](#)

# Monotone Bounds: Women who Remain Childless

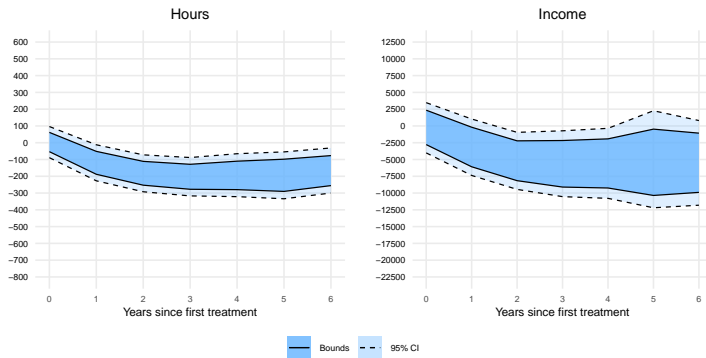


Figure 39: Monotone bounds using final status

[Back](#)

# Relaxing Monotonicity to Partnered Women

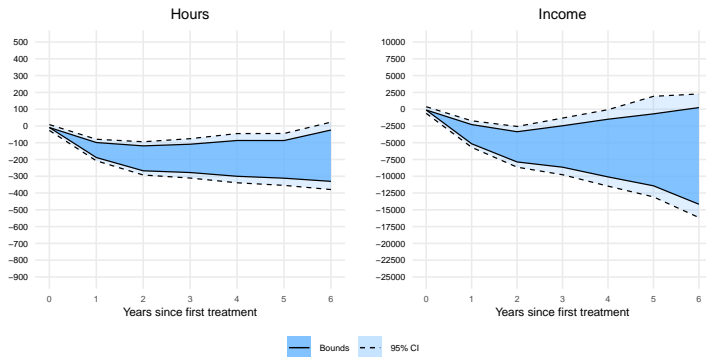


Figure 40: Monotone bounds using women who stay partnered

[Back \(extensions\)](#)

[Back \(monotonicity\)](#)

# Testing the Plug-in Approach

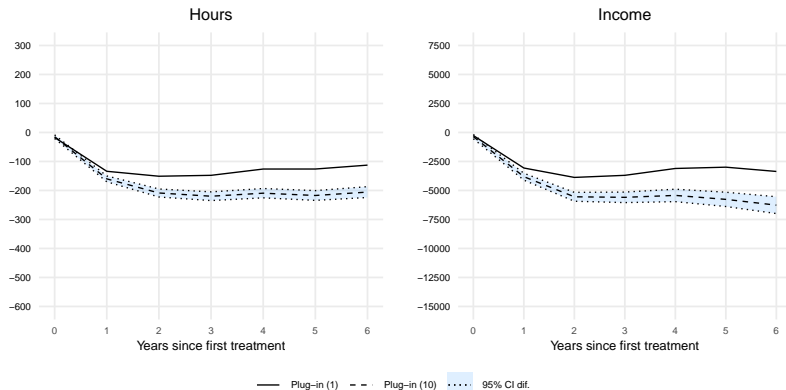


Figure 41: Plug-in estimators exploiting different number of treatments

[Back](#)

# Application to Other Settings

Key features:

1. Dynamic treatment effects.
2. Individuals (may choose to) “re-apply” for random treatment assignment.
3. Some may obtain treatment endogenously.



# Application to Other Settings

Key features:

1. Dynamic treatment effects.
2. Individuals (may choose to) “re-apply” for random treatment assignment.
3. Some may obtain treatment endogenously.

Few examples:

- Education, medical trials, research grants, job training.

Examples

# Application to Other Settings (Examples)

- ▶ Education: grade retention, school admission lotteries, special and gifted education programs.
- ▶ Medical trials: individuals assigned to control may eventually choose to participate in other medical trials or selectively receive a different treatment.
- ▶ Research grants: after unsuccessful application can apply for another or receive funding other ways.
- ▶ Job training: those not assigned to training may re-apply, some assignments may be non-random.

[Back](#)

# Estimated Bias and Placebo Event Study

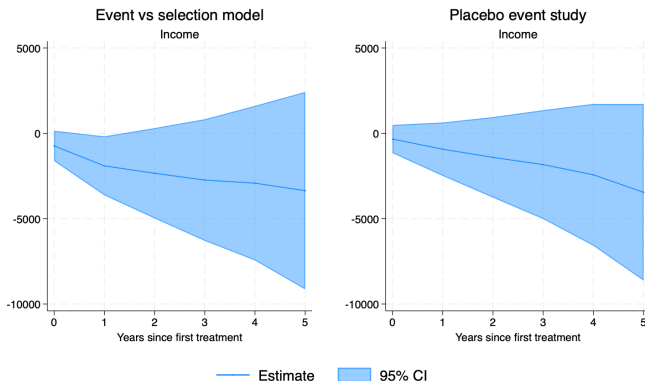


Figure 42: Difference between selection model estimate and event study estimate compared to placebo event study estimate

# References I

- Agüero, J. M., & Marks, M. S. (2008). Motherhood and female labor force participation: evidence from infertility shocks. *American Economic Review*, 98(2), 500–504.
- Angelov, N., Johansson, P., & Lindahl, E. (2016). Parenthood and the gender gap in pay. *Journal of labor economics*, 34(3), 545–579.
- Angrist, J., & Evans, W. N. (1996). *Children and their parents' labor supply: Evidence from exogenous variation in family size*. National bureau of economic research Cambridge, Mass., USA.
- Bensnes, S., Huitfeldt, I., & Leuven, E. (2023). *Reconciling estimates of the long-term earnings effect of fertility* (Tech. Rep.). Institute of Labor Economics (IZA).
- Bertrand, M. (2011). New perspectives on gender. In *Handbook of labor economics* (Vol. 4, pp. 1543–1590). Elsevier.
- Bertrand, M. (2020). Gender in the twenty-first century. In *Aea papers and proceedings* (Vol. 110, pp. 1–24).
- Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of economic literature*, 55(3), 789–865.
- Bronars, S. G., & Grogger, J. (1994). The economic consequences of unwed motherhood: Using twin births as a natural experiment. *The American Economic Review*, 1141–1156.
- Brooks, N., & Zohar, T. (2021). *Out of labor and into the labor force? the role of abortion access, social stigma, and financial constraints* (Tech. Rep.).
- Chung, Y., Downs, B., Sandler, D. H., Sienkiewicz, R., et al. (2017). *The parental gender earnings gap in the united states* (Tech. Rep.).
- Cristia, J. P. (2008). The effect of a first child on female labor supply: Evidence from women seeking fertility services. *Journal of Human Resources*, 43(3), 487–510.
- Cruces, G., & Galiani, S. (2007). Fertility and female labor supply in latin america: New causal evidence. *Labour Economics*, 14(3), 565–573.
- Eichmeyer, S., & Kent, C. (2022). *Parenthood in poverty*. Centre for Economic Policy Research.
- Gallen, Y., Joensen, J. S., Johansen, E. R., & Veramendi, G. F. (2023). The labor market returns to delaying pregnancy. *Available at SSRN 4554407*.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American economic review*, 104(4), 1091–1119.

# References II

- Han, S. (2021). Identification in nonparametric models for dynamic treatment effects. *Journal of Econometrics*, 225(2), 132–147.
- Heckman, J. J., Humphries, J. E., & Veramendi, G. (2016). Dynamic treatment effects. *Journal of econometrics*, 191(2), 276–292.
- Hirvonen, L. (2009). *The effect of children on earnings using exogenous variation in family size: Swedish evidence*.
- Hotz, V. J., McElroy, S. W., & Sanders, S. G. (2005). Teenage childbearing and its life cycle consequences: Exploiting a natural experiment. *Journal of Human Resources*, 40(3), 683–715.
- Iacovou, M. (2001). *Fertility and female labour supply* (Tech. Rep.). ISER Working Paper Series.
- Jacobsen, J. P., Pearce III, J. W., & Rosenbloom, J. L. (1999). The effects of childbearing on married women's labor supply and earnings: using twin births as a natural experiment. *Journal of Human Resources*, 449–474.
- Kaplan, J. (2023, October 9). A woman's chance for equal pay plummets when she has a kid — and never recovers, says the newest harvard economist to win the nobel prize. *Business Insider*. Retrieved from <https://www.businessinsider.com/women-pay-gap-motherhood-fatherhood-nobel-prize-harvard-economist-2023-10>
- Kleven, H., Landais, C., & Leite-Mariante, G. (2023). *The child penalty atlas* (Tech. Rep.). National Bureau of Economic Research.
- Kleven, H., Landais, C., Posch, J., Steinhauer, A., & Zweimüller, J. (2019). Child penalties across countries: Evidence and explanations. In *Aea papers and proceedings* (Vol. 109, pp. 122–126).
- Kleven, H., Landais, C., & Søgaaard, J. E. (2019). Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, 11(4), 181–209.
- Lee, D. S. (2005). *Training, wages, and sample selection: Estimating sharp bounds on treatment effects*. National Bureau of Economic Research Cambridge, Mass., USA.
- Lundborg, P., Plug, E., & Rasmussen, A. W. (2017). Can women have children and a career? IV evidence from IVF treatments. *American Economic Review*, 107(6), 1611–37.
- Maurin, E., & Moschion, J. (2009). The social multiplier and labor market participation of mothers. *American Economic Journal: Applied Economics*, 1(1), 251–272.

# References III

- Melentyeva, V., & Riedel, L. (2023). *Child penalty estimation and mothers' age at first birth* (Tech. Rep.). ECONtribute Discussion Paper.
- Miller, A. R. (2011). The effects of motherhood timing on career path. *Journal of population economics*, 24, 1071–1100.
- Miller, C. C. (2017, May 13). The gender pay gap is largely because of motherhood. *The New York Times*. Retrieved from <https://www.nytimes.com/2017/05/13/upshot/the-gender-pay-gap-is-largely-because-of-motherhood.html>
- Rosenzweig, M. R., & Wolpin, K. I. (1980). Life-cycle labor supply and fertility: Causal inferences from household models. *Journal of Political economy*, 88(2), 328–348.
- Semenova, V. (2020). Generalized lee bounds. *arXiv preprint arXiv:2008.12720*.
- Van den Berg, G. J., & Vikström, J. (2022). Long-run effects of dynamically assigned treatments: A new methodology and an evaluation of training effects on earnings. *Econometrica*, 90(3), 1337–1354.
- Vere, J. P. (2011). Fertility and parents' labour supply: new evidence from us census data: Winner of the oep prize for best paper on women and work. *Oxford Economic Papers*, 63(2), 211–231.
- Zhang, J. L., & Rubin, D. B. (2003). Estimation of causal effects via principal stratification when some outcomes are truncated by “death”. *Journal of Educational and Behavioral Statistics*, 28(4), 353–368.