Bounding the Career Cost of Parenthood

Julius Ilciukas

University of Amsterdam

Motivation

The differential impact of parenthood on the careers of women and men is widely suspected to be a major cause of gender disparities in the labor market.

Motivation

The differential impact of parenthood on the careers of women and men is widely suspected to be a major cause of gender disparities in the labor market.

- "Not surprisingly, children are the main contributors to women's labor supply changes." (Goldin, 2014)
- "Parenthood has sharply asymmetric impacts on labor market outcomes between the genders, depressing mothers' earnings while leaving fathers' earnings essentially unchanged." (Bertrand, 2020)
- "...the remaining gender disparities in labor market outcomes are related to the fact that children impose significantly larger penalties on the career trajectories of women compared to men."(Cortés & Pan, 2023)
- "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 the time of becoming a parent

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 the time of becoming a parent

Leading methods address one or the other

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, & Søgaard, 2019):

Age 35, 1st child at 30	Age 35, 1st child at 36

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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison** ⟷	Age 35, 1st child at 36

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, & Søgaard, 2019):

Age 35, 1st child at 30	← **Direct comparison** →	Age 35, 1st child at 36
All mothers for 5 years		**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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison** ⟷	Age 35, 1st child at 36
All mothers for 5 years		**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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison** ⟷	Age 35, 1st child at 36
All mothers for 5 years		**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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison**	Age 35, 1st child at 36
All mothers for 5 years		**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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison** ⟷	Age 35, 1st child at 36
All mothers for 5 years		**All childless**

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

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

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

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, & Søgaard, 2019):

Age 35, 1st child at 30	⟷ **Direct comparison** ⟷	Age 35, 1st child at 36
All mothers for 5 years		**All childless**

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

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

Age 35, 1st IVF at 30 worked	⟷ **IV for parenthood at 35** ⟷	Age 35, 1st IVF at 30 failed

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, & Søgaard, 2019):

Age 35, 1st child at 30	**Direct comparison** ⟷	Age 35, 1st child at 36
All mothers for 5 years		**All childless**

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

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

Age 35, **1st IVF at 30** worked	**IV for parenthood at 35** ⟷	Age 35, **1st IVF at 30** failed

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, & Søgaard, 2019):

Age 35,
1st child at 30

Direct comparison

Age 35,
1st child at 36

All mothers for 5 years

All childless

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

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

Age 35,
1st IVF at 30 worked

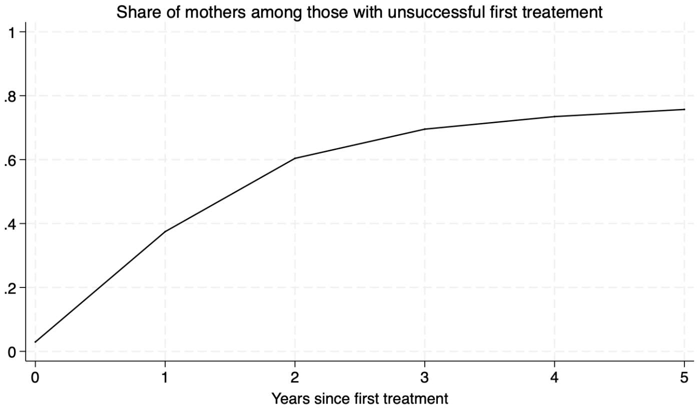
IV for parenthood at 35

Age 35,
1st IVF at 30 failed

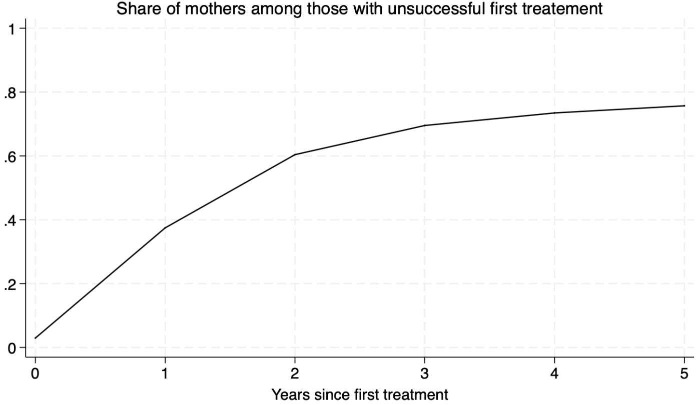
All mothers for 5 years

Some childless, some mothers for <5 years

Motherhood After 1st ACP fails

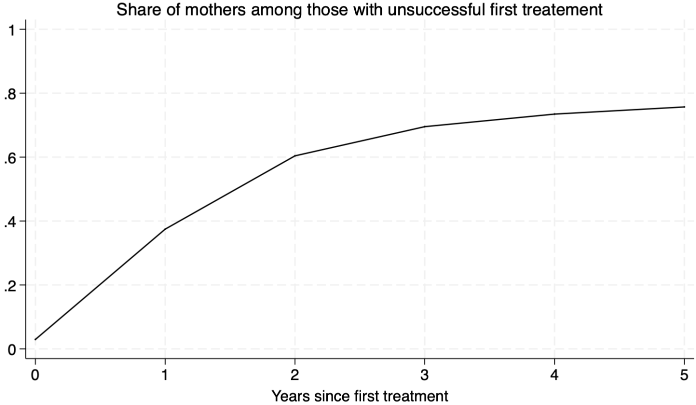


Motherhood After 1st ACP fails



$$\tau_{RF} = 0.25\tau_{Parenthood} + 0.75\tau_{Ealier}$$

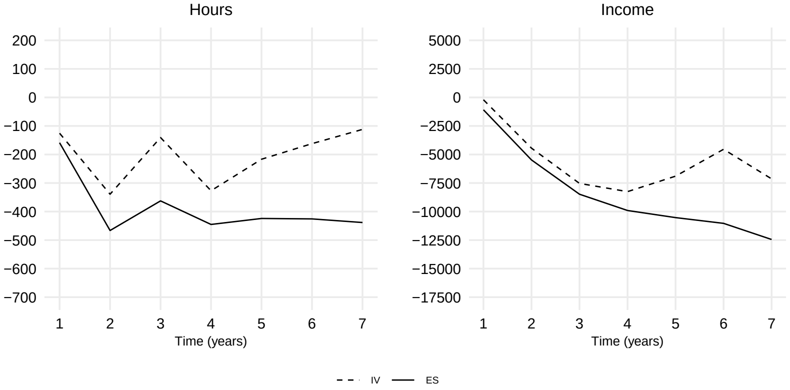
Motherhood After 1st ACP fails



$$\tau_{RF} = 0.25\tau_{Parenthood} + 0.75\tau_{Ealier}$$

$$\tau_{IV} = \tau_{Parenthood} + 3\tau_{Ealier}$$

IV vs ES



ES extern.

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

This Paper

1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
   - IVF, IUI
2. Empirical evidence using Dutch data

This Paper

1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
    - IVF, IUI
2. Empirical evidence using Dutch data

- 1^{st} try mothers vs 1^{st} fail & childless
- Challenge: childless women are a selective group

This Paper

1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
   - IVF, IUI
2. Empirical evidence using Dutch data

- 1^{st} try mothers vs 1^{st} fail & childless
- Challenge: childless women are a selective group
  1. Use full ACP histories to account for selection via ACPs
  2. Bounding to address remaining births

This Paper

1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
    - IVF, IUI
2. Empirical evidence using Dutch data

- 1^{st} try mothers vs 1^{st} fail & childless
- Challenge: childless women are a selective group
    1. Use full ACP histories to account for selection via ACPs
    2. Bounding to address remaining births
- Only crucial assumption: (cond.) random ACP outcomes
    - Endogenous # of attempts & non-ACP fertility
    - No parametric ass. (Bensnes et al., 2023; Gallen et al., 2023)

This Paper

1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
   - IVF, IUI
2. Empirical evidence using Dutch data

- 1^{st} try mothers vs 1^{st} fail & childless
- Challenge: childless women are a selective group
  1. Use full ACP histories to account for selection via ACPs
  2. Bounding to address remaining births
- Only crucial assumption: (cond.) random ACP outcomes
  - Endogenous # of attempts & non-ACP fertility
  - No parametric ass. (Bensnes et al., 2023; Gallen et al., 2023)
- External validity
  - Extrapolation to when women choose to remain childless
  - Extrapolation to non-ACP families

Model

Model

- Particular moment since woman's first ACP attempt

Model

- Particular moment since woman's first ACP attempt
- Outcome when motherhood begins at first ACP attempt:

Model

- Particular moment since woman's first ACP attempt
- Outcome when motherhood begins at first ACP attempt:

$$Y(1)$$

Model

- Particular moment since woman's first ACP attempt
- Outcome when motherhood begins at first ACP attempt:

$$Y(1)$$

- Childless outcome:

$$Y(0)$$

Model

- Particular moment since woman's first ACP attempt
- Outcome when motherhood begins at first ACP attempt:

$$Y(1)$$

- Childless outcome:

$$Y(0)$$

- Outcome when motherhood begins after first ACP attempt:

$$Y(later)$$

Counterfactuals discussion

Model (cont.)

Model (cont.)

Women differ in:

- Willingness to undergo ACP, W
  - Would try W times in case all attempts fail (integer)

Model (cont.)

Women differ in:

- Willingness to undergo ACP, W
  - Would try W times in case all attempts fail (integer)
- Reliance on ACP, R
  - No child if ALL ACPs fail (dummy)
  - "Reliers" $\supseteq$ "compliers" (no child if first ACP fails)

Model (cont.)

Women differ in:

- Willingness to undergo ACP, W
  - Would try W times in case all attempts fail (integer)
- Reliance on ACP, R
  - No child if ALL ACPs fail (dummy)
  - "Reliers" $\supseteq$ "compliers" (no child if first ACP fails)
- **Both are endogenous but independent of success:**

Model (cont.)

Women differ in:

- Willingness to undergo ACP, W
  - Would try W times in case all attempts fail (integer)
- Reliance on ACP, R
  - No child if ALL ACPs fail (dummy)
  - "Reliers" $\supseteq$ "compliers" (no child if first ACP fails)
- **Both are endogenous but independent of success:**

$$(Y(1), Y(0), R, W) \perp D_j | A \geq j$$

- A - 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"

Treatment Effect

$$\tau_{ATR} = \mathbb{E}[Y(1) - Y(0) | R = 1]$$

- Average treatment effect for women reliant on ACP

Simple World: Max 1 ACP, All Reliers

Simple World: Max 1 ACP, All Reliers

$$W = 1$$
(willing to try once)

Simple World: Max 1 ACP, All Reliers

$W = 1$
(willing to try once)

$D_1 = 1$

$D_1 = 0$

Simple World: Max 1 ACP, All Reliers

$W = 1$
(willing to try once)

$D_1 = 1$

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

$D_1 = 0$

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

Simple World: Max 2 ACPs, All Reliers

Simple World: Max 2 ACPs, All Reliers

$W = 1$
(willing to try once)

$D_1 = 1$

$D_1 = 0$

Simple World: Max 2 ACPs, All Reliers

$W = 1$
(willing to try once)

$D_1 = 1$

$D_1 = 0$

$W = 2$
(willing to try twice)

$D_1 = 1$

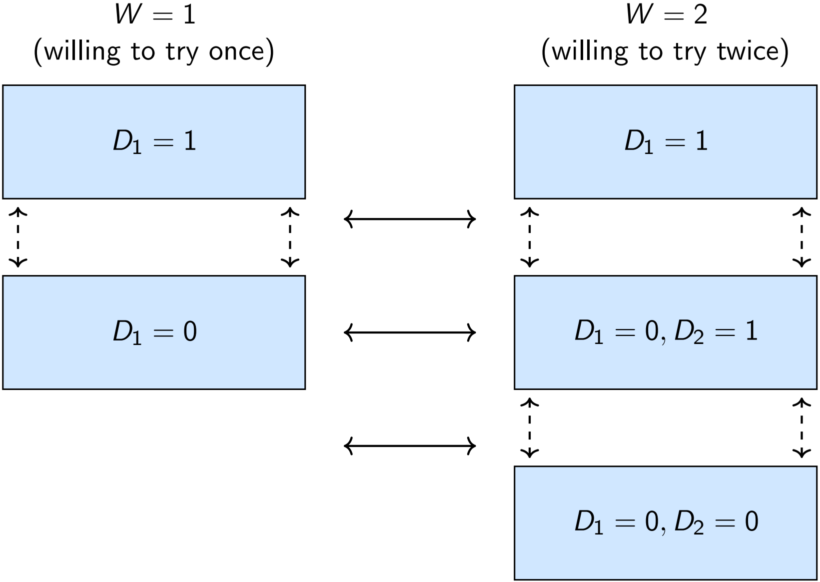
$D_1 = 0, D_2 = 1$

$D_1 = 0, D_2 = 0$

Simple World: Max 2 ACPs, All Reliers

$W = 1$ (willing to try once)		$W = 2$ (willing to try twice)
$D_1 = 1$		$D_1 = 1$
	$\longleftrightarrow$	
$D_1 = 0$	$\longleftrightarrow$	$D_1 = 0, D_2 = 1$
	$\longleftrightarrow$	
		$D_1 = 0, D_2 = 0$

Simple World: Max 2 ACPs, All Reliers



Simple World: Max 2 ACPs, All Reliers

$W = 1$
(willing to try once)

$D_1 = 1$

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

$D_1 = 0$

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

$W = 2$
(willing to try twice)

$D_1 = 1$

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

$D_1 = 0, D_2 = 1$

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

$D_1 = 0, D_2 = 0$

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

Simple World (Observed): Max 2 Attempts, All Reliers

$W = 1$ (willing to try once)	$W = 2$ (willing to try twice)
$D_1 = 1$	$D_1 = 1$
$D_1 = 0$	$D_1 = 0, D_2 = 1$
	$D_1 = 0, D_2 = 0$

Simple World (Observed): Max 2 Attempts, All Reliers

$W = 1$
(willing to try once)

$W = 2$
(willing to try twice)

$D_1 = 1$

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

$D_1 = 0$

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

$D_1 = 0, D_2 = 1$

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

$D_1 = 0, D_2 = 0$

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

Simple World (Observed): Max 2 Attempts, All Reliers

$W = 1$
(willing to try once)

$W = 2$
(willing to try twice)

$D_1 = 1$

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

$D_1 = 0$

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

$D_1 = 0, D_2 = 1$

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

$D_1 = 0, D_2 = 0$

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

Simple World (Observed): Max 2 Attempts, All Reliers

$W = 1$
(willing to try once)

$W = 2$
(willing to try twice)

$D_1 = 1$

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

$D_1 = 0$

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

$D_1 = 0, D_2 = 1$

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

$D_1 = 0, D_2 = 0$

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

$Pr(W = 1) =$

Simple World: Max 1 ACP with Non-reliers

Simple World: Max 1 ACP with Non-reliers

$W = 1$

$R = 1$
(no child if fail)

$R = 0$
(child if fail)

Simple World: Max 1 ACP with Non-reliers

$W = 1$

$R = 1$
(no child if fail)

$R = 0$
(child if fail)

$D_1 = 1$

Simple World: Max 1 ACP with Non-reliers

$W = 1$

$R = 1$
(no child if fail)

$R = 0$
(child if fail)

$D_1 = 1$

$D_1 = 0, C = 0$

$D_1 = 0, C = 1$

Simple World: Max 1 ACP with Non-reliers

$W = 1$

$R = 1$
(no child if fail)

$R = 0$
(child if fail)

$D_1 = 1$

$D_1 = 0, C = 0$

$D_1 = 0, C = 1$

$Pr(R = 1) =$

Simple World: Max 1 ACP with Non-reliers

$W = 1$

$R = 1$
(no child if fail)

$R = 0$
(child if fail)

$D_1 = 1$

$F_{Y(1)}$

$D_1 = 0, C = 0$

$D_1 = 0, C = 1$

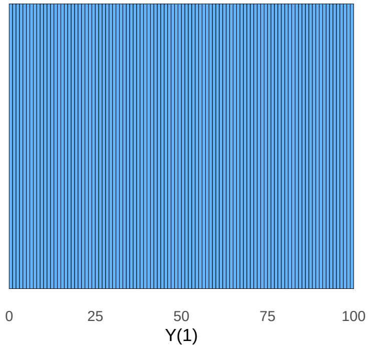
$Pr(R = 1) =$

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

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

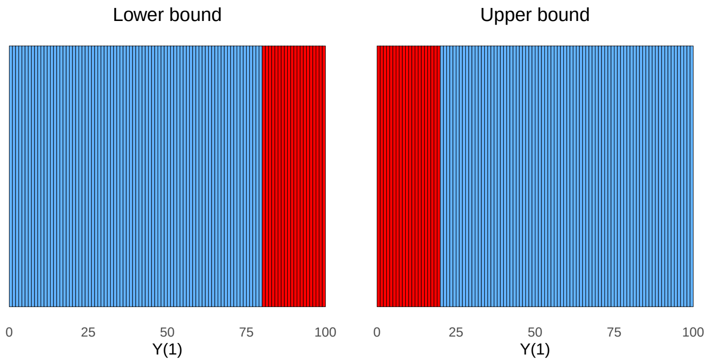
Intuition: Motherhood Outcome $Y(1)$

1. Distribution of motherhood outcomes using women with successful first ACP



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

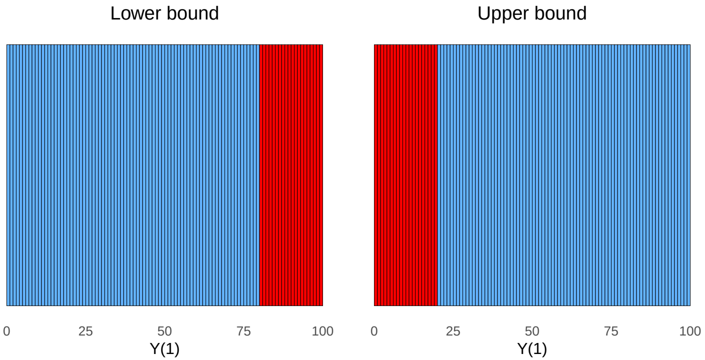
2. Estimate $\Pr(R=1) = 0.8$ on control group
3. Assume most extreme distributions of types



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

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

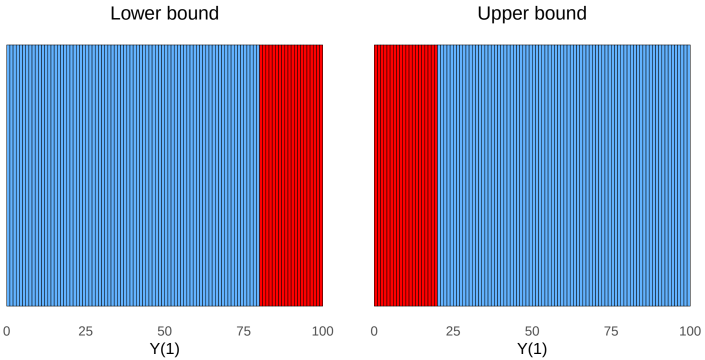
$$LB_{\mathbb{E}[Y(1)|R=1]} \leq \mathbb{E}[Y(1)|R=1] \leq UB_{\mathbb{E}[Y(1)|R=1]}$$



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

5. Bounds on the effect:

$$LB_{\tau_{ATR}} \leq \mathbb{E}[Y(1) - Y(0)|R = 1] \leq UB_{\tau_{ATR}}$$



Using covariates Estimator

Assisted Conception Procedures

Assisted Conception Procedures

In vitro fertilization (IVF)

- Relatively invasive procedure performed under sedation/anesthesia
- $\sim$25% success rate

Assisted Conception Procedures

In vitro fertilization (IVF)

- Relatively invasive procedure performed under sedation/anesthesia
- $\sim$25% success rate

Intrauterine insemination (IUI)

- Sperm injected directly into the uterus.
- $\sim$10% success rate
- First-line infertility treatment in most countries

Assisted Conception Procedures

In vitro fertilization (IVF)

- Relatively invasive procedure performed under sedation/anesthesia
- $\sim$25% success rate

Intrauterine insemination (IUI)

- Sperm injected directly into the uterus.
- $\sim$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
- 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

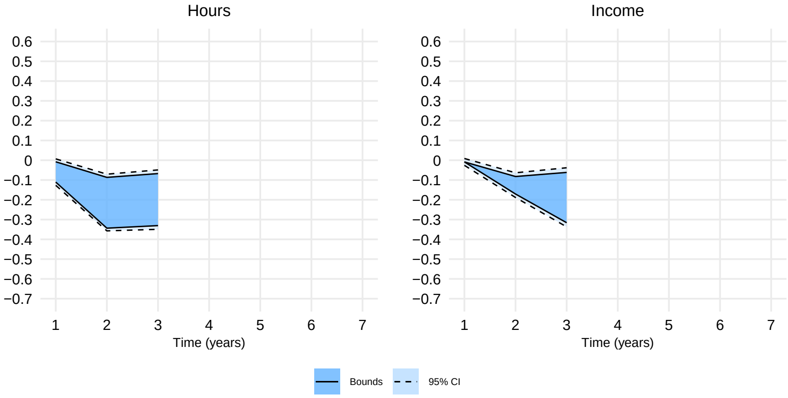


Figure 1: Bounds - short run

Baseline Lee bounds Absolute effects

Bounds

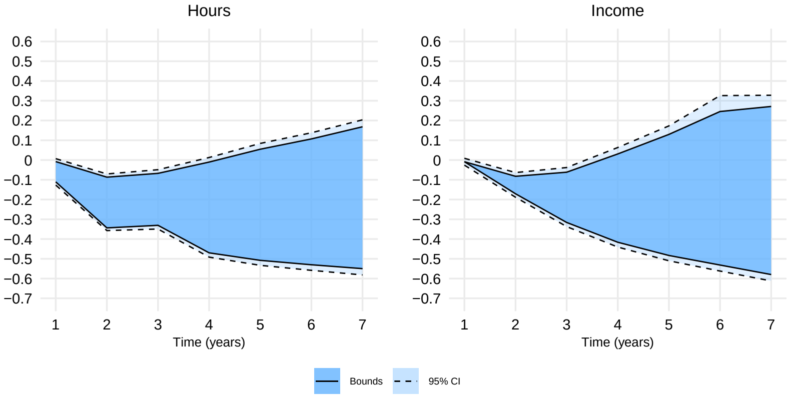


Figure 2: Bounds - medium run

Baseline Lee bounds Absolute effects

Monotonicity

Monotonicity

- Some women whose first ACP succeeds eventually conceive more children without ACP

Monotonicity

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

Plausibility discussion | Benefit of monotonicity | Graphic intuition

Monotone Bounds

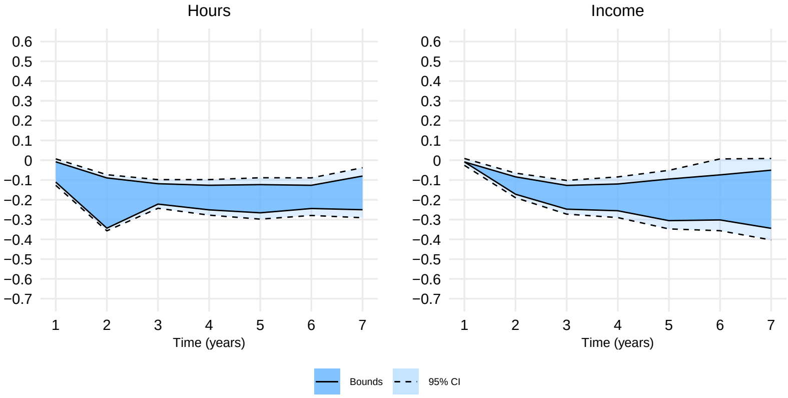


Figure 3: Monotone bounds for percent effects

Absolute How wide?

Monotone Bounds: Gender Inequality

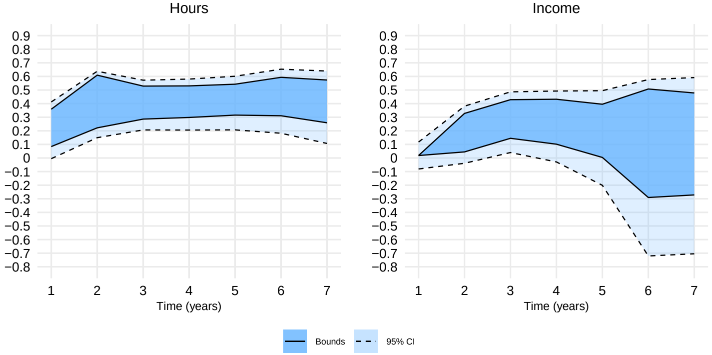


Figure 4: Share of gender inequality explained by parenthood

Extensions

Outcomes:

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

Existing estimators:

- Are existing estimates biased? Naive IV-IVF equiv. Plac. ES Place. ineq.
- Are estimates less informative that existing? Confidence intervals

Robustness:

- Bias due to depression Counterfact. Depr. effect Bounds non-depr. Arguments
- 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. Mother. imp. Childless imp. Effect imp. Gap

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 for 7 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 for 7 years
  - Drives up to 56% (44%) 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 for 7 years
  - Drives up to 56% (44%) 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 for 7 years
  - Drives up to 56% (44%) 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 for 7 years
  - Drives up to 56% (44%) 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

Bensnes et al. (2023); Gallen et al. (2023)

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

ToC

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: 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

ToC

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 (model) Back (extensions) Depr. effect Bounds non-depr. Arguments

Identification Intuition (cont.)

Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0,P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j] \\ &= \mathbb{E}[Y(0)|R=1, W=j]\end{aligned}$$

Identification Intuition (cont.)

Step 0:

$$\mathbb{E}[Y|C=0,P=j] = \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j] \\ = \mathbb{E}[Y(0)|R=1, W=j]$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|R=1],$$

Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0,P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j] \\ &= \mathbb{E}[Y(0)|R=1, W=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|R=1],$$

with:

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

ToC

Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0,P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j] \\ &= \mathbb{E}[Y(0)|R=1, W=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|R=1],$$

with:

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

Step 2:

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

Identification Intuition (cont.)

Step 0:

$$\begin{aligned}\mathbb{E}[Y|C=0,P=j] &= \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j] \\ &= \mathbb{E}[Y(0)|R=1, W=j]\end{aligned}$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|R=1],$$

with:

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

Step 2:

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

Step 3:

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

Identification Intuition (cont.)

Step 0:

$$\mathbb{E}[Y|C=0,P=j] = \mathbb{E}[Y(0)|j \text{ fails}, R=1, W=j]$$
$$= \mathbb{E}[Y(0)|R=1, W=j]$$

Step 1:

$$\mathbb{E}[w(P)Y|C=0] = \mathbb{E}[Y(0)|R=1],$$

with:

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

Step 2:

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

Step 3:

1. Y's among $D_1 = 1$ "reveal" the distribution of $Y(1)'s$
2. Assume women with $R = 1$ are in the left/right tail
3. Bounds on $\mathbb{E}[Y(1)|R=1]$ Graph int. Coins Det. int Trimming int. Back

ToC

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

ToC

Formal Identification

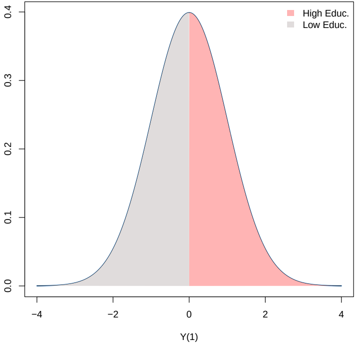
$$\Delta_L = \mu_L - \mu_C$$
$$\Delta_U = \mu_U - \mu_C$$
$$\mu_C = \mathbb{E}\left[\frac{Y}{\prod_j^P (1 - p_j(X_j))}\middle|\mathbf{1}_{Child} = 0\right] \mathbb{E}\left[\prod_j^P (1 - p_j(X_j))\middle|\mathbf{1}_{Child} = 0\right]$$
$$\mu_L = \mathbb{E}\left[\frac{Y}{p_1(X_1)}\middle|D_1 = 1, Y < y(1-s)\right] \mathbb{E}\left[p_1(X_1)|D_1 = 1, Y < y(1-s)\right]$$
$$\mu_U = \mathbb{E}\left[\frac{Y}{p_1(X_1)}\middle|D_1 = 1, Y > y(s)\right] \mathbb{E}\left[p_1(X_1)|D_1 = 1, Y > y(s)\right]$$
$$y(q) = G^{-1}(q)$$
$$G(q) = \mathbb{E}\left[\frac{\mathbf{1}(Y \le q)}{p_1(X_1)}\middle|D_1 = 1\right] \mathbb{E}[p_1(X_1)|D_1 = 1]$$
$$s = \mathbb{E}\left[\frac{\mathbf{1}_{Child}}{\prod_j^P (1 - p_j(X_j))}\middle|W = 0\right] \mathbb{E}\left[\prod_j^P (1 - p_j(X_j))\middle|W = 0\right],$$

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

Back

Tightening Bounds with Covariates

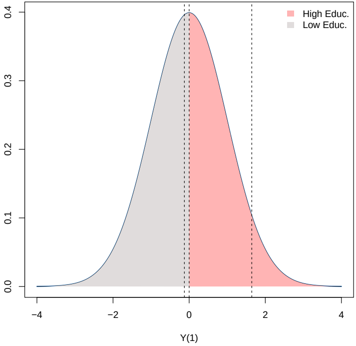
1. Separate distribution of motherhood outcomes into low and high education groups



ToC

Tightening Bounds with Covariates (cont.)

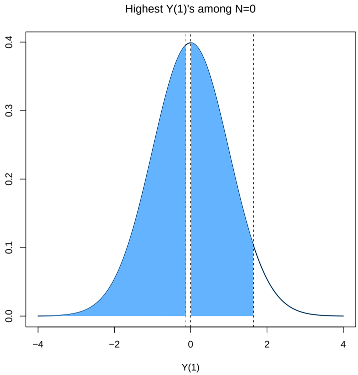
2. Estimate $\Pr(R = 1|high) = 0.9$ and $\Pr(R = 1|low) = 0.9$ on control group
3. Assume most extreme distribution of types within educ. groups



Tightening Bounds with Covariates (cont.)

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

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

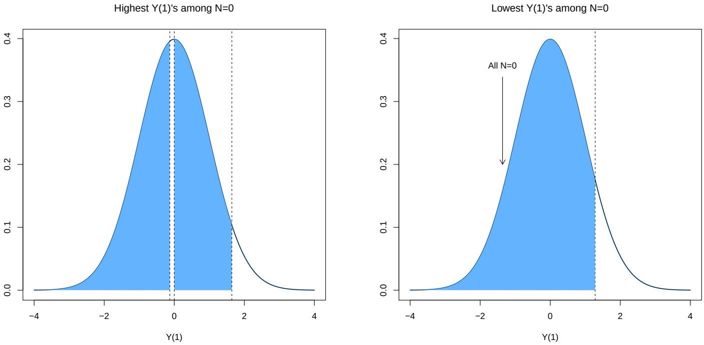


ToC

Comparing the Bounds

Conditional lower bounds is higher than unconditional:

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

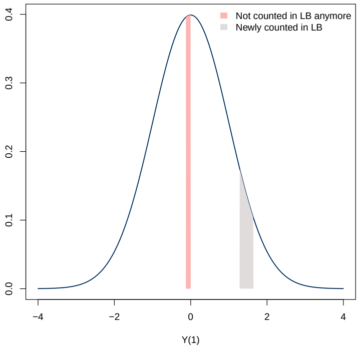


ToC

Comparing the Bounds (cont.)

Conditional lower bounds is higher than unconditional:

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



Estimation

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

Estimation

$$
\begin{aligned}
m_L(data, \eta_0) &= \underbrace{\frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}}}_{\text{1st success mean below trim thresh.}} - \underbrace{\Pi_{j=1}^{P} \frac{1 - D_j}{1 - e_j(X_j)} SY}_{\text{childless mean}} \\
\eta_0 &= \{s_0(x), q_1(u, x), e_1(x), \ldots, e_J(x)\} \\
s_0(x) &= Pr(R = 1 | X_1 = x) \\
q_1(u, x) &= F^{-1}_{Y(1)|X_1 = x}(u) \\
e_j(x) &= Pr(D_j = 1 | P \geq j, X_j = x) \\
S &= 1_{\{childless\}}
\end{aligned}
$$

Estimation

$$
\begin{aligned}
m_L(data, \eta_0) &= \underbrace{\frac{D_1}{e_1(X_1)} Y 1_{\{Y < q_1(s_0(X_1), X_1)\}}}_{\text{1st success mean below trim thresh.}} - \underbrace{\Pi_{j=1}^{P} \frac{1 - D_j}{1 - e_j(X_j)} SY}_{\text{childless mean}} \\
\eta_0 &= \{s_0(x), q_1(u, x), e_1(x), \ldots, e_J(x)\} \\
s_0(x) &= Pr(R = 1 | X_1 = x) \\
q_1(u, x) &= F^{-1}_{Y(1)|X_1 = x}(u) \\
e_j(x) &= Pr(D_j = 1 | P \geq j, X_j = x) \\
S &= 1_{\{childless\}}
\end{aligned}
$$

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

Estimation

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

$$\eta_0 = \{s_0(x), q_1(u, x), e_1(x), \ldots, e_J(x)\}$$

$$s_0(x) = Pr(R = 1 | X_1 = x)$$

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

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

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

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

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

Inference

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

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

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

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

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

ToC

Inference

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

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

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

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

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

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

Narrowing the Bounds with Covariates (cont.)

Alternative extension of Lee bounds (to my knowledge)

- Take some function $g(x)$
- $\mathbb{E}[g(X_1)|R = 1]$ can be identified on women who remain childless
- Take $\mathbb{E}[Y(1)|R = 1] = \mathbb{E}[g(X_1) + \varepsilon|R = 1]$
- Only need to bound $\mathbb{E}[\varepsilon|R = 1]$
- $g(X_1)$ 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, $\mathbb{E}[g(X_1)|R = 1]$ 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

Balance

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	0.863	0.018	0.008
	[0.324]	[0.344]	(0.009)	(0.009)
Work (P)	0.884	0.865	0.019	0.014
	[0.320]	[0.341]	(0.009)	(0.009)
Hours (W)	1239.696	1208.255	31.441	17.578
	[605.070]	[634.840]	(16.168)	(15.812)
Hours (P)	1473.383	1438.880	34.502	22.690
	[658.917]	[695.345]	(17.699)	(17.587)
Income 1000s € (W)	28.049	27.434	0.615	0.942
	[19.559]	[20.232]	(0.516)	(0.496)
Income 1000s € (P)	37.173	36.959	0.214	0.896
	[26.484]	[29.443]	(0.746)	(0.732)
Bachelor deg. (W)	0.608	0.605	0.002	0.018
	[0.488]	[0.489]	(0.013)	(0.012)
Bachelor deg. (P)	0.593	0.598	-0.004	0.008
	[0.491]	[0.490]	(0.013)	(0.012)
Age (W)	31.643	32.384	-0.741	
	[4.016]	[4.383]	(0.111)	
Age (P)	34.672	35.459	-0.787	
	[5.527]	[5.993]	(0.152)	
Observations	1,716	13,788		
Joint *p*-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	-0.002	0.023	0.008	0.030	0.007	-0.008	0.016	0.041
	(0.009)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)	(0.017)	(0.019)	(0.026)
Work (P)	0.011	0.014	0.005	0.014	-0.004	-0.008	0.001	0.016	0.040
	(0.010)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)	(0.017)	(0.020)	(0.027)
Hours (W)	37.050	-0.615	45.477	39.327	68.596	25.780	-5.734	81.149	29.860
	(17.373)	(18.648)	(20.127)	(21.930)	(24.489)	(26.043)	(31.176)	(36.869)	(49.101)
Hours (P)	29.074	28.347	18.441	35.597	-7.332	-15.344	0.360	47.511	49.279
	(19.336)	(20.807)	(22.614)	(24.685)	(27.215)	(28.618)	(34.381)	(41.158)	(55.440)
Income 1000s € (W)	1.786	0.283	1.123	1.672	1.380	0.489	0.417	1.839	-0.297
	(0.548)	(0.592)	(0.647)	(0.710)	(0.786)	(0.831)	(1.030)	(1.240)	(1.714)
Income 1000s € (P)	0.221	1.277	1.588	1.125	-0.542	-0.370	1.567	1.001	-0.202
	(0.820)	(0.846)	(0.923)	(1.018)	(1.123)	(1.212)	(1.423)	(1.666)	(2.277)
Bachelor deg. (W)	0.002	0.026	-0.020	0.001	-0.003	0.003	0.023	-0.012	0.045
	(0.013)	(0.014)	(0.015)	(0.017)	(0.019)	(0.020)	(0.024)	(0.028)	(0.038)
Bachelor deg. (P)	0.005	0.010	0.011	0.007	-0.003	0.013	0.020	0.012	-0.014
	(0.013)	(0.014)	(0.016)	(0.017)	(0.019)	(0.020)	(0.024)	(0.029)	(0.039)
Age (W)	0.001	-0.007	-0.040	0.024	0.013	-0.001	-0.046	-0.027	-0.017
	(0.011)	(0.015)	(0.019)	(0.023)	(0.026)	(0.028)	(0.036)	(0.043)	(0.059)
Age (P)	0.001	-0.007	-0.040	0.024	0.013	-0.001	-0.046	-0.027	-0.017
	(0.011)	(0.015)	(0.019)	(0.023)	(0.026)	(0.028)	(0.036)	(0.043)	(0.059)
Observations	12,955	10,759	8,714	6,969	5,403	3,938	2,718	1,848	1,173
Joint *p*-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.

Back

ToC

Representative and Relevant Treatment group

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

	Success (1)	Fail (2)	Reliers (3)	Representative (4)	Success vs rep. (1)-(4)	Rel. vs rep. (3)-(4)
Work (W)	0.882	0.863	0.820	0.800	0.082	0.020
	[0.323]	[0.344]	[0.335]	[0.400]	(0.010)	(0.005)
Work (P)	0.884	0.865	0.849	0.782	0.103	0.068
	[0.320]	[0.342]	[0.345]	[0.413]	(0.010)	(0.005)
Hours (W)	1240.315	1207.860	1117.711	1068.897	171.418	48.815
	[604.666]	[635.194]	[584.369]	[698.712]	(16.915)	(8.442)
Hours (P)	1474.530	1438.590	1390.699	1242.166	232.364	148.533
	[658.231]	[695.692]	[663.944]	[794.776]	(19.241)	(9.591)
Income 1000s € (W)	28.065	27.418	24.976	20.846	7.219	4.130
	[19.559]	[20.219]	[15.080]	[17.990]	(0.436)	(0.218)
Income 1000s € (P)	37.205	36.952	35.299	27.471	9.734	7.828
	[26.482]	[29.452]	[23.982]	[28.686]	(0.694)	(0.346)
Bachelor deg. (W)	0.480	0.451	0.398	0.411	0.069	-0.012
	[0.500]	[0.498]	[0.411]	[0.492]	(0.012)	(0.006)
Bachelor deg. (P)	0.394	0.381	0.329	0.345	0.049	-0.015
	[0.489]	[0.486]	[0.397]	[0.475]	(0.012)	(0.006)
Age (W)	31.638	32.388	33.480	28.375	3.263	5.105
	[4.015]	[4.383]	[3.896]	[4.657]	(0.113)	(0.056)
Age (P)	34.675	35.461	36.580	28.375	6.300	8.205
	[5.513]	[5.996]	[3.927]	[4.663]	(0.113)	(0.057)
Observations	1,714	13,809	4,882	376,157		

Note: Labor market outcomes measured year before first treatment for main sample and year and 9 months before birth of first child for represenstative sample. Representative sample selected to match main sample by year of conception. Relier sample consists of women who remain childless 7 years after their first ART attempt with weights described under implementation. (W) - woman, (P) - partner. Standard deviations in brackets. Standard errors in parentheses.

Back

ToC

Predicted Success Prob. per Treatment

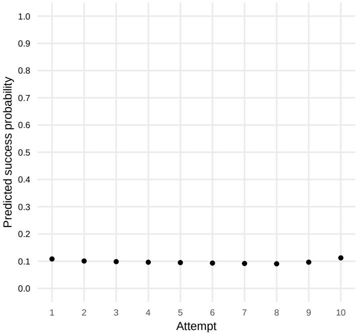


Figure 5: Predicted success probability holding X fixed at first attempt average

Back

Attempts

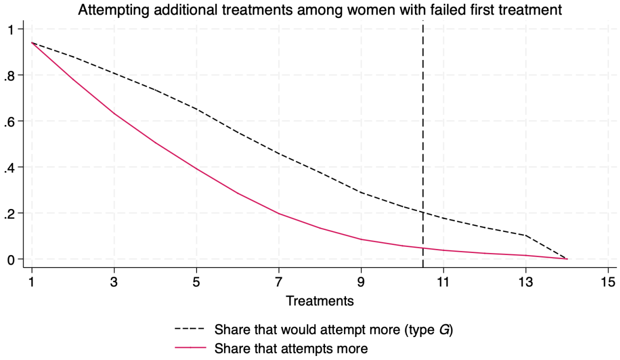


Figure 6: Number of treatments and type

Back

Non-treatment Conception by Type

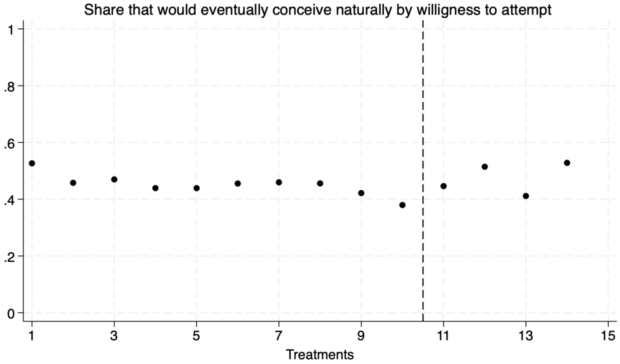


Figure 7: Conceiving naturally and willingness to attempt

Back

ToC

Trimming shares

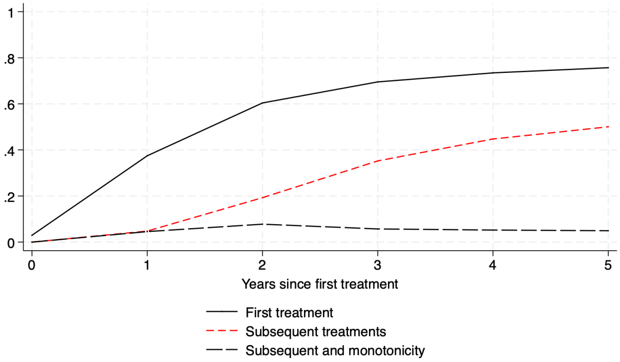


Figure 8: Trimming share under different information

Back

Correction Term

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

Back

ToC

Bounds: Absolute

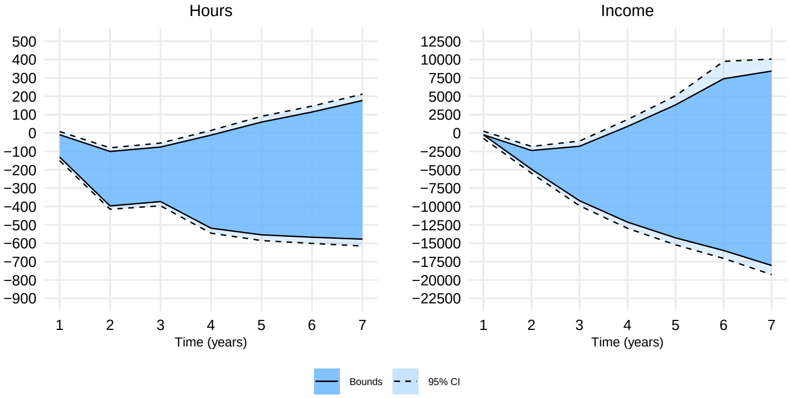


Figure 9: Bounds effects

Back

ToC

Bounds: Hours - Comparison to Baseline Lee Bounds

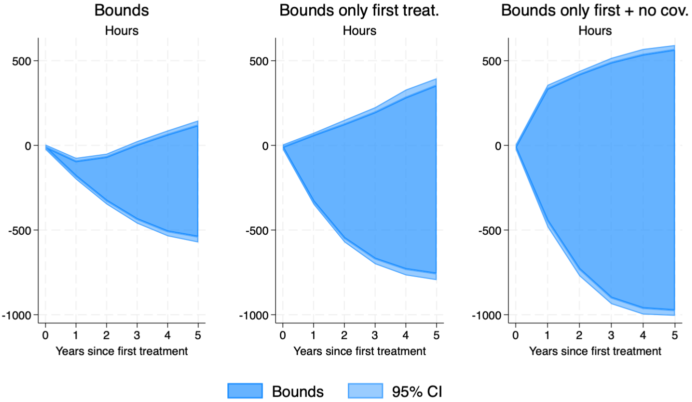


Figure 10: Comparison with baseline Lee: hours

Back

ToC

Bounds: Income - Comparison to Baseline Lee Bounds

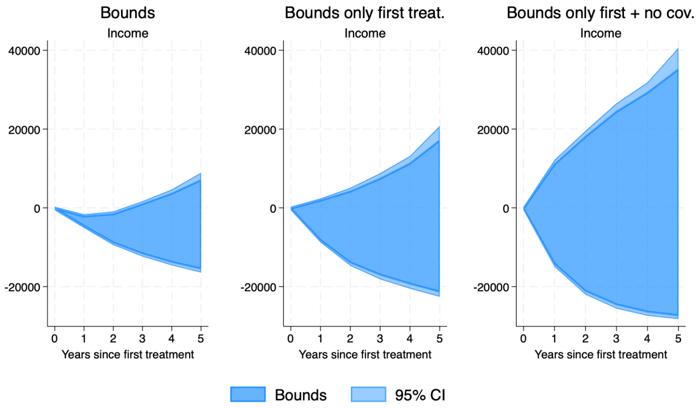


Figure 11: Comparison with baseline Lee: income

Back

ToC

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

ToC

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:

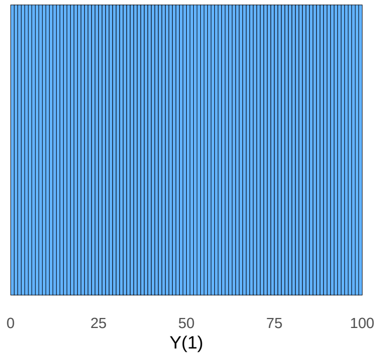


Figure 12: Distribution of potential motherhood outcomes

Back

ToC

Monotonicity: Intuition (2)

Without monotonicity: 20 with highest/lowest outcomes:

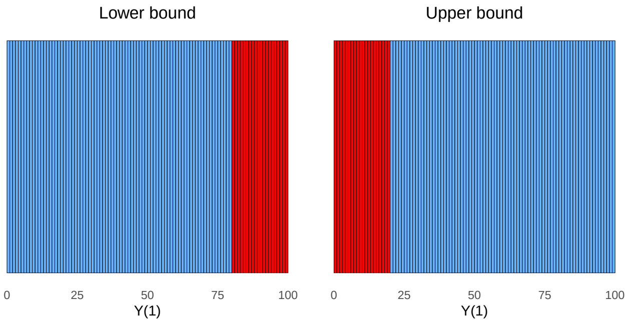


Figure 13: Distribution of potential motherhood outcomes

Back

Monotonicity: Intuition (3)

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

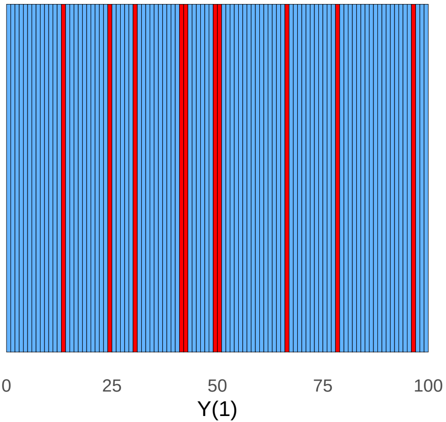


Figure 14: Distribution of potential motherhood outcomes

Monotonicity: Intuition (4)

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

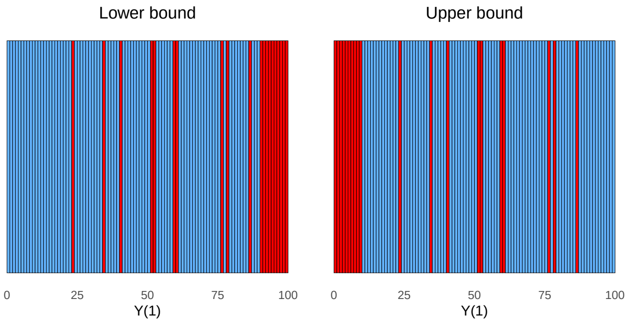


Figure 15: Distribution of potential motherhood outcomes

Back

Monotonicity: Intuition (5)

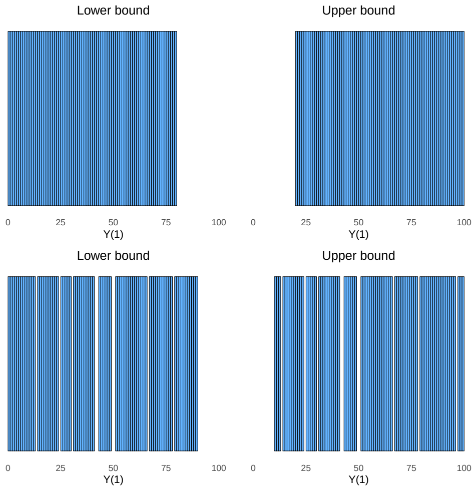


Figure 16: Distribution of potential motherhood outcomes

Monotone Bounds: Absolute

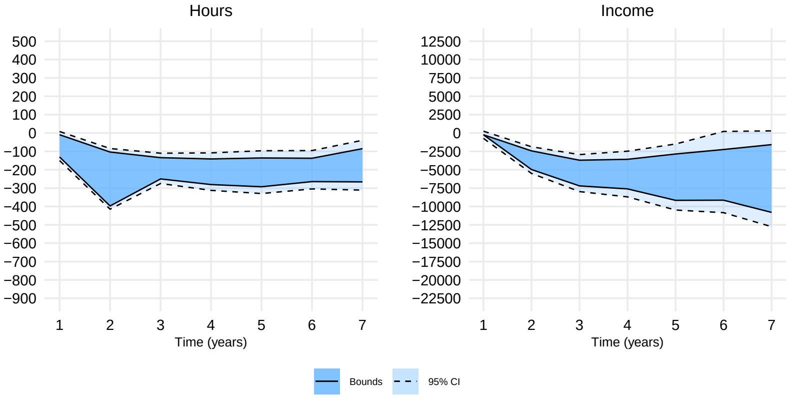


Figure 17: Monotone bounds: absolute terms

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

Existing estimators:

- Are existing estimates biased? Naive IV-IVF equiv. Plac. ES Place. ineq.
- Are estimates less informative that existing? Confidence intervals

Robustness:

- Bias due to depression Counterfact. Depr. effect Bounds non-depr. Arguments
- 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. Mother. imp. Childless imp. Effect imp. Gap

Monotone Bounds: Women who Remain Childless

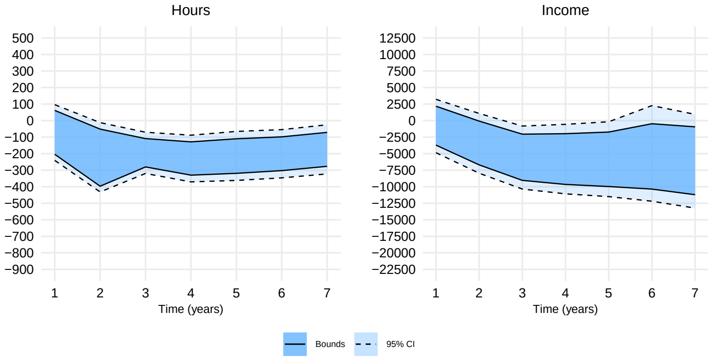


Figure 18: Monotone bounds using final status

Back

Event Study: Population vs IUI Sample

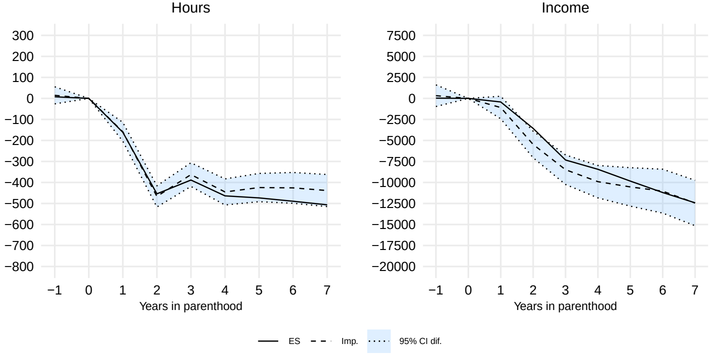


Figure 19: ES for population and women with first IUI success

Back (extensions) Back (intro)

Imputing Population Motherhood Outcomes Using IUI Sample

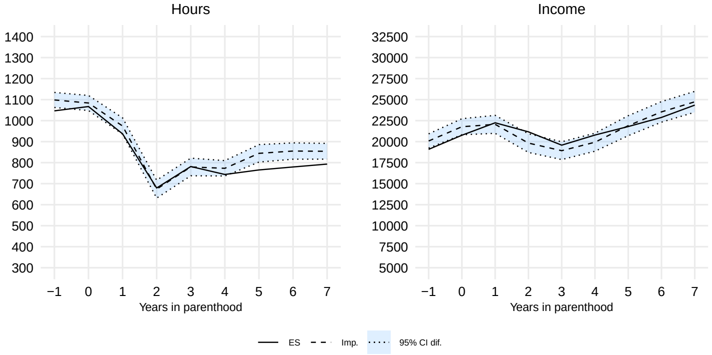


Figure 20: Population Outcomes vs IUI-imputation (age & education)

Back

ToC

Imputing Population Childless Outcomes Using IUI Sample

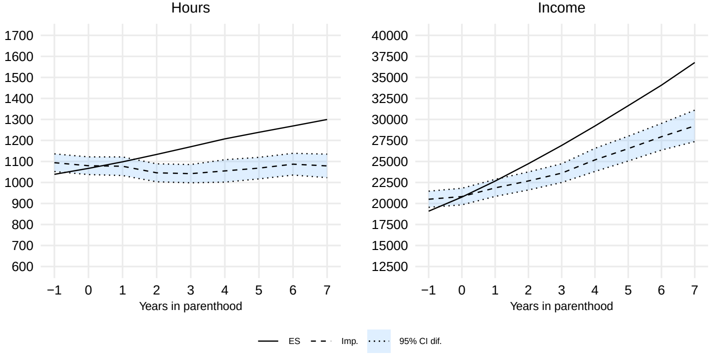


Figure 21: Population Outcomes vs IUI-imputation (age & education)

Back

ToC

Event Study vs IUI-imputation for Population

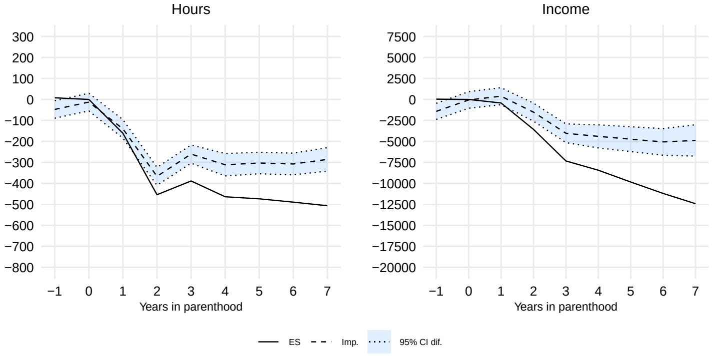


Figure 22: Event study vs IUI-imputation for population (age & education)

Back

ToC

Event Study vs IUI-imputation: Inequality

$$\text{Ineq. cause by children} = \frac{\tau}{\text{Ineq. w/o children} + \tau}$$

Event Study vs IUI-imputation: Inequality

$$\text{Ineq. cause by children} = \frac{\tau}{\text{Ineq. w/o children} + \tau}$$

Event Study vs IUI-imputation: Inequality

$$\text{Ineq. cause by children} = \frac{\tau}{\color{red}{\text{Ineq. w/o children}} + \tau}$$

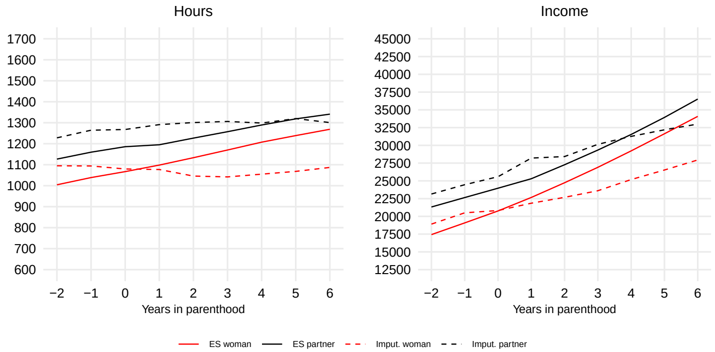
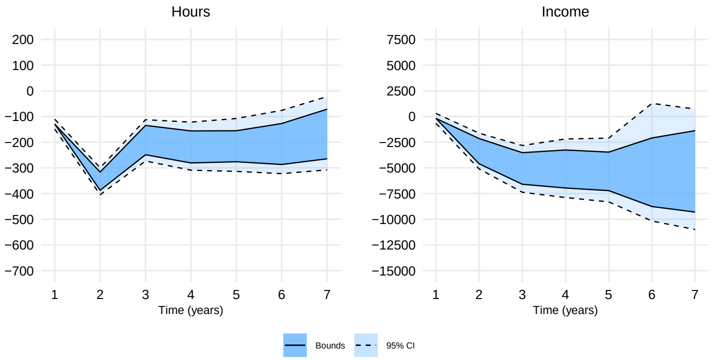


Figure 23: Event study vs IUI-imputation for population gaps (age & education), partner outcomes shifted 3 years

ToC

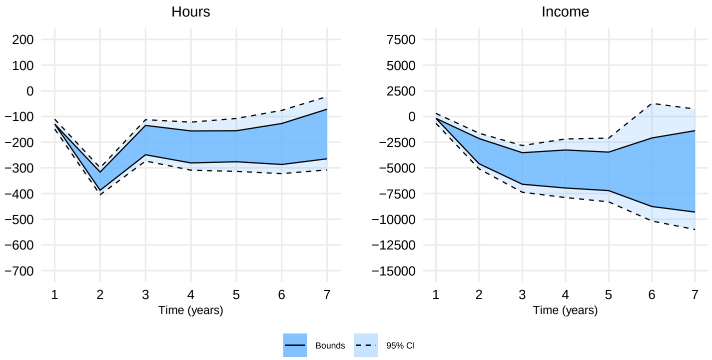
Back

Simple estimator



Back

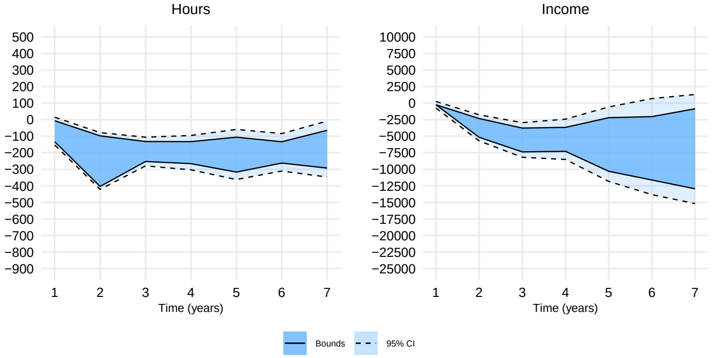
Simple estimator



Back

ToC

Relaxing Monotonicity Direction



Back

ToC

Heterogeneity by Covariates

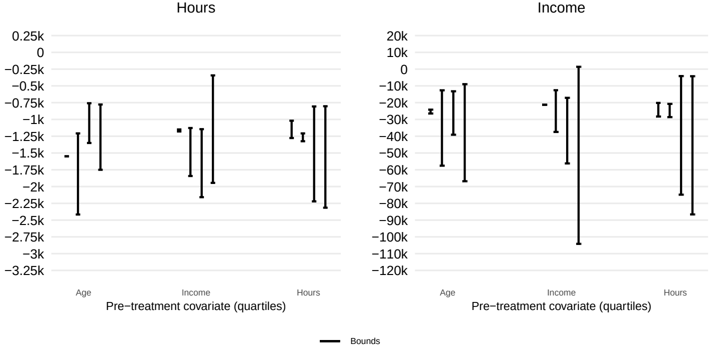


Figure 24: Cumulative outcomes after 6 years, pre-treatment covariates

Back

ToC

Heterogeneity by Willingness to Undergo Procedures

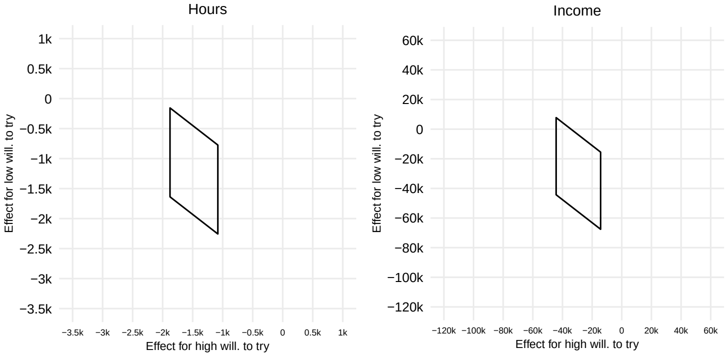


Figure 25: Cumulative outcomes 6 years after, G above or below 6

Back

ToC

Monotone Bounds: Excluding Depression

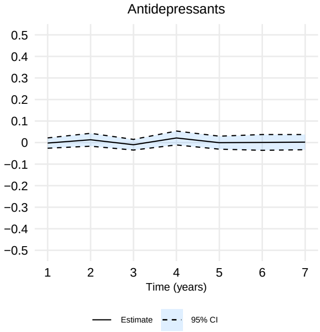


Figure 26: Sequential-IV estimates for effect on antidepressant take-up

Back (extensions) Back (model)

ToC

Monotone Bounds: Excluding Depressed

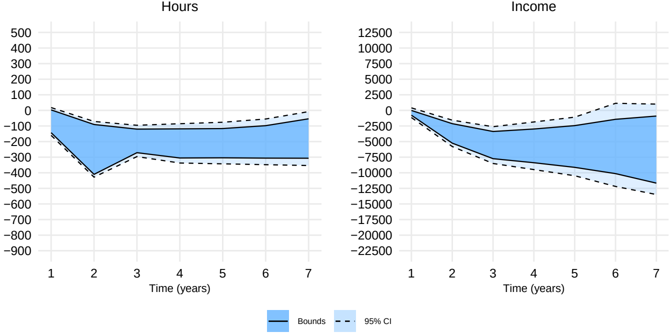


Figure 27: Monotone bounds for women who would not start antidepressants if they were to remain childless

Back (extensions) Back (model)

ToC

Arguments Regarding Mental Health

- Mental health consequences of not having a child are arguably a part of the relevant counterfactual
- IUI is significantly less invasive than IVF
- "Effects" of severe health shocks (including mental health shocks and psychical shocks that are followed by invasive treatments) are "relatively" small
- Partners' mental health might also suffer, which could alleviate concerns for inequality estimates

Back (extensions) Back (model)

ToC

Monotone Bounds: Assuming Maximum Leave

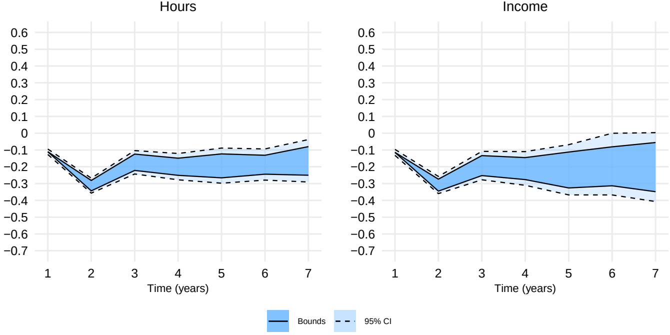


Figure 28: Monotone bounds scaling outcomes in years with childbirth by max. leave fraction

Back

ToC

Monotone Bounds: Correcting for Partner's age

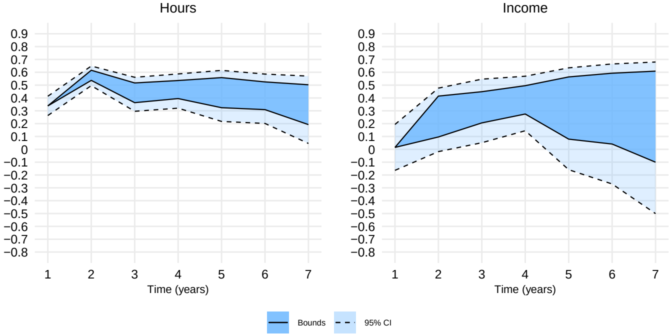


Figure 29: Monotone bounds using male income at same age as female

Back

ToC

Monotone Bounds: Fatherhood Penalty

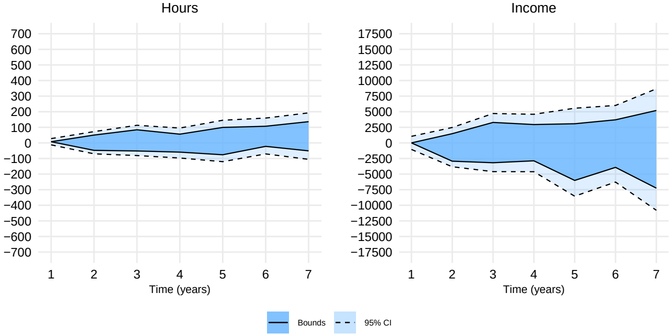


Figure 30: Monotone bounds for partners

Back

Monotone Bounds: Fatherhood Penalty in Percent

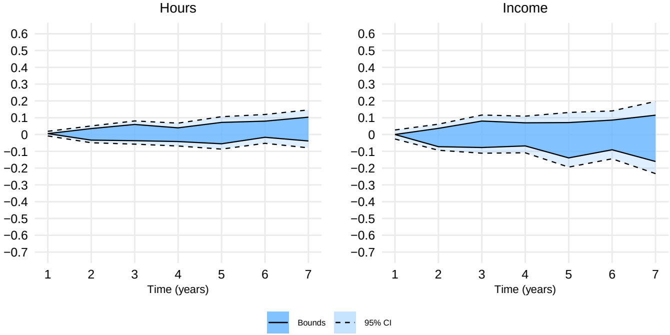


Figure 31: Monotone bounds for partners in percent

Back

ToC

Monotone Bounds: Explaining Gender Inequality

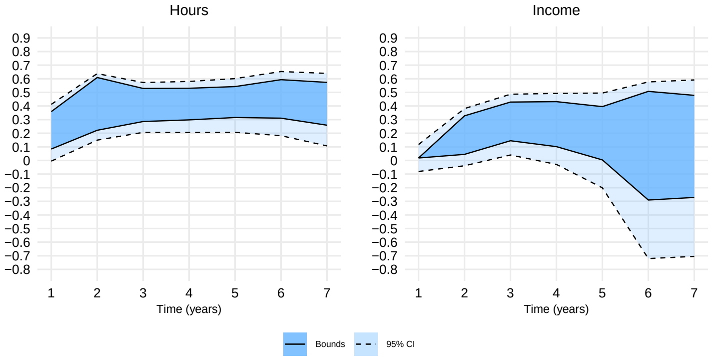


Figure 32: Share of gender inequality explained by parenthood

Back

ToC

Are Bounds Less Informative?

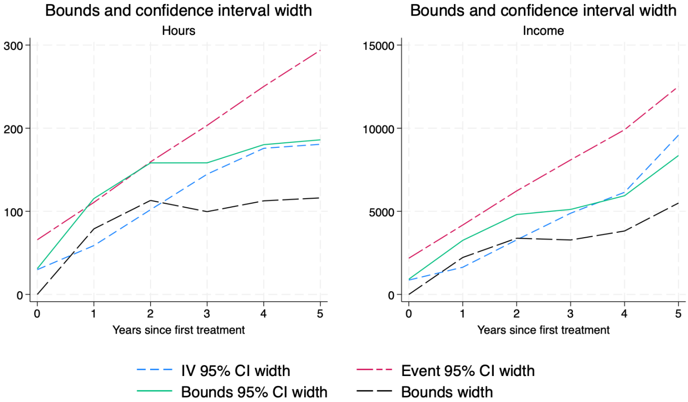


Figure 33: Confidence intervals for different methods

Back

ToC

Naive Comparison

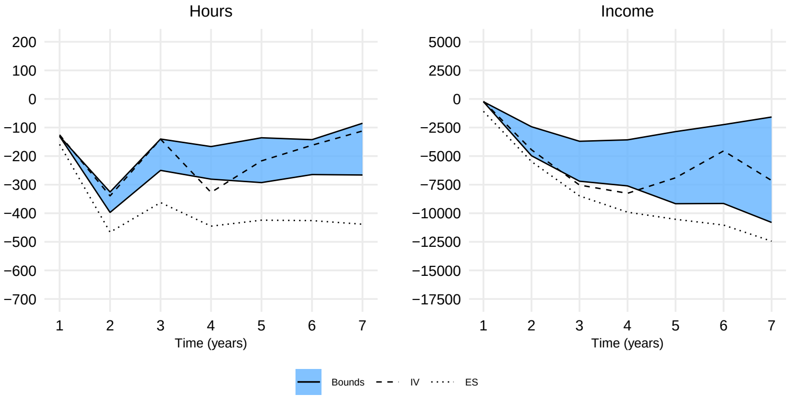


Figure 34: Estimates based on different methods

IV→women with lowest treated hours get children after ACPs fail Back

ToC

Monotone Bounds and IV

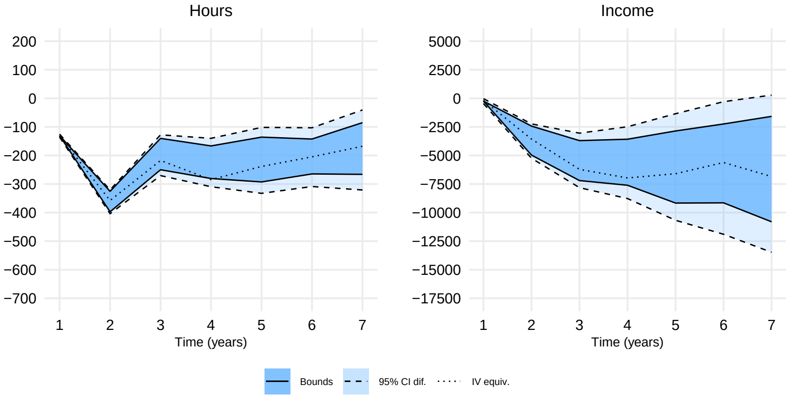


Figure 35: Bounds and IV equivalent for the same population

Back

ToC

Placebo Event

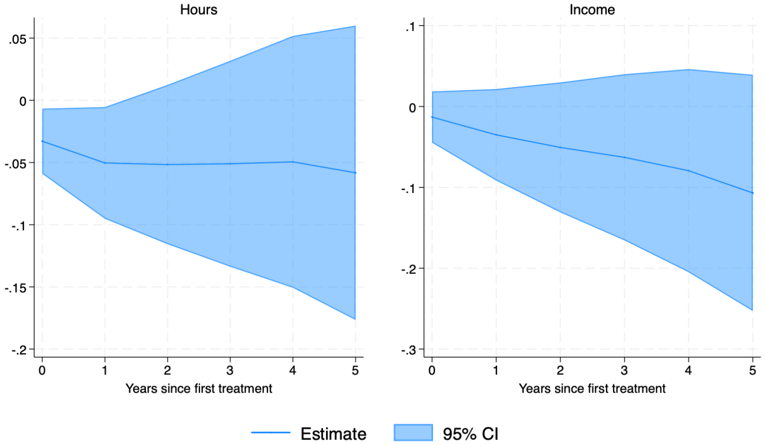


Figure 36: Placebo event study

ToC Back Placebo as causal

Inequality treating ES bias as causal

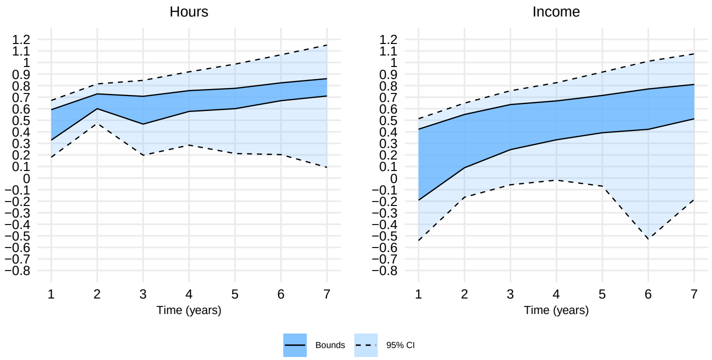


Figure 37: Placebo effects as share of bounds for the same population

Two possible interpretations:

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

Back

Yearly effect of Delaying Motherhood

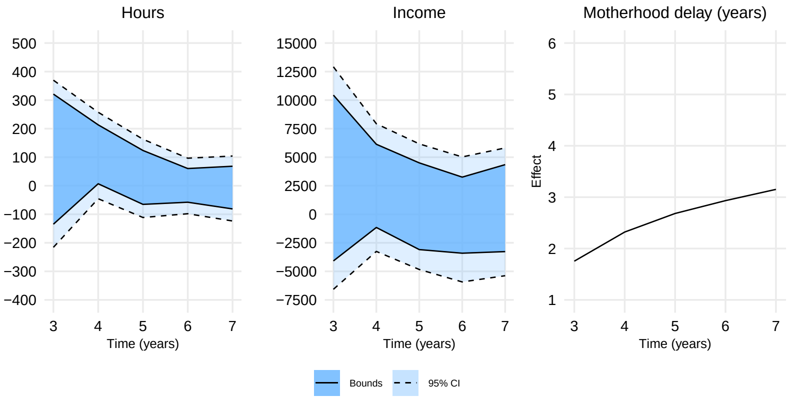


Figure 38: Effect of delaying relative to motherhood at first attempt

Opposite of what is frequently assumed!

Back

Cumulative effect of Delaying Motherhood

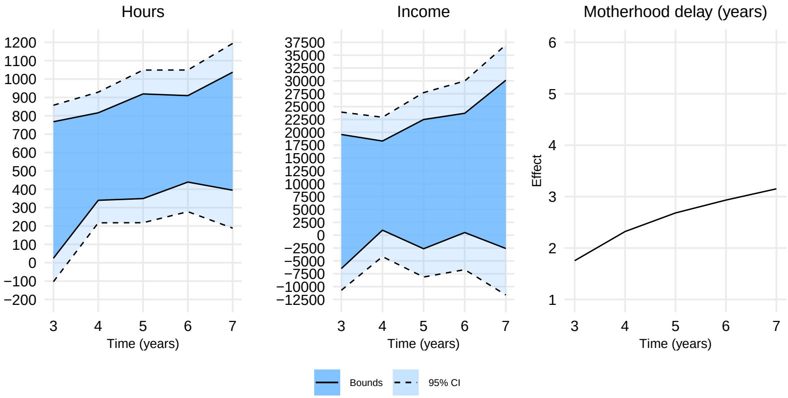


Figure 39: Effect of delaying relative to motherhood at first attempt

Back

ToC

Monotone Bounds: Women who Remain Childless

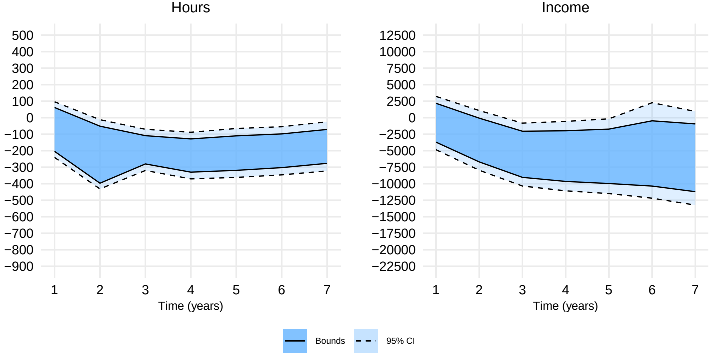


Figure 40: Monotone bounds using final status

Back

Relaxing Monotonicity to Partnered Women

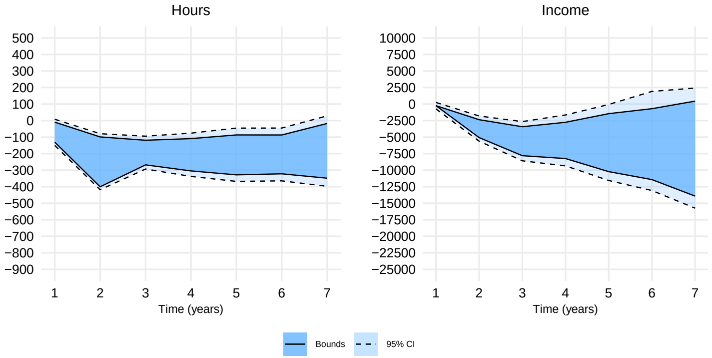


Figure 41: Monotone bounds using women who stay partnered

Back (extensions) Back (monotonicity)

ToC

Testing the Plug-in Approach

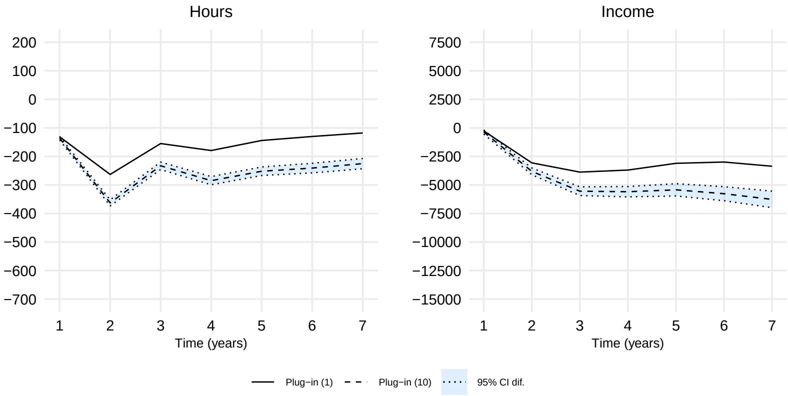


Figure 42: Plug-in estimators exploiting different number of treatments

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.

ToC

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

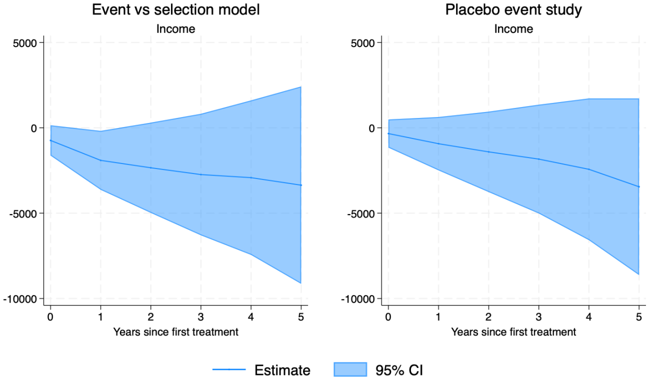


Figure 43: Difference between selection model estimate and event study estimate compared to placebo event study estimate

Back

ToC

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.).

Cortés, P., & Pan, J. (2023). Children and the remaining gender gaps in the labor market. *Journal of Economic Literature*, *61*(4), 1359–1409.

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.

References II

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.

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.

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., & Søgaard, 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.

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.