Career Cost of Parenthood, Selective Fertility, and Dynamic Effects

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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)

Causal Identification Challenge

Fertility is endogenous

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

Effects of parenthood are dynamic

- Time spent in parenthood, career stage and age at the time of becoming a parent, number and age of children,

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)

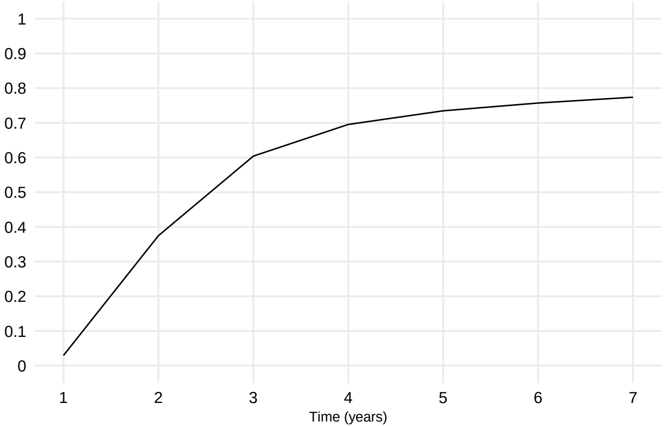
Event study (Kleven, Landais, & Søgaard, 2019):

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

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

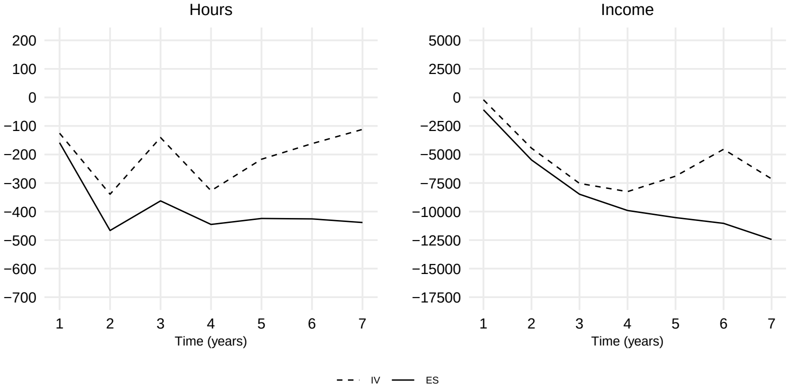
Motherhood After 1st Procedure Fails



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

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

IV vs ES



ES extern.

This Paper

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- Only crucial assumption: (cond.) random ACP outcomes
    - Endogenous # of attempts & non-ACP fertility
    - No parametric ass. (Bensnes et al., 2023; Gallen et al., 2023)

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  - 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

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

$$Y(1)$$

- Childless outcome:

$$Y(0)$$

- Outcome when motherhood begins after first ACP:

$$Y(later)$$

Counterfactuals discussion

Model (cont.)

Women differ in:

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

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Parameter of interest:

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

Assumption

Assumption (Sequential Unconfoundedness)

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

- A - number of attempts
- D_j - success of attempt j

In words: once sperm/eggs at ACP j are implanted, whether this results in a conception is as-good-as-random

- $e = \Pr(D_j = 1 | A \geq j)$ for all j for illustration.

Intuition: Childless Outcome $Y(0)$

1. Childless women $\subset$ reliers
2. Selective subgroup ONLY due to unobs. willing. to try ACPs
   - Cond. on W relier fertility is as good as random
   - Reliers with higher W underrepresented

$$\Pr(C = 0 | R = 1, W = w) = (1 - e)^{W}$$

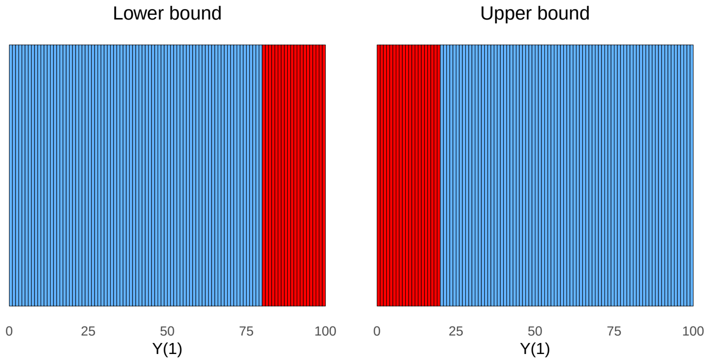
3. Observed number of ACPs is sufficient to account for it
   - Among childless $A = W$
   - Higher weights to women who tried more

$$\mathbb{E}\left[Y \frac{(1 - C)}{(1 - e)^{A}}\right] = \mathbb{E}\left[Y(0) | R = 1\right] \Pr(R = 1)$$

$$\mathbb{E}\left[\frac{(1 - C)}{(1 - e)^{A}}\right] = \Pr(R = 1),$$

Intuition: Motherhood Outcome $Y(1)$

1. Treated group is a rep. sample but their types are unobserved
2. Identify $\Pr(R = 1) = 0.8$ on control group
3. Assume most extreme distributions of types in treated group
4. Bound $\mathbb{E}[Y(1)|R = 1]$



Background

Assisted conception procedures

- IUI (primary procedure): sperm injected into uterus
- IVF (secondary procedure): embryo inserted into uterus

Data

- Dutch administrative data
- Labor market outcomes from 2011 to 2022

ACPs Data

Results: Bounds

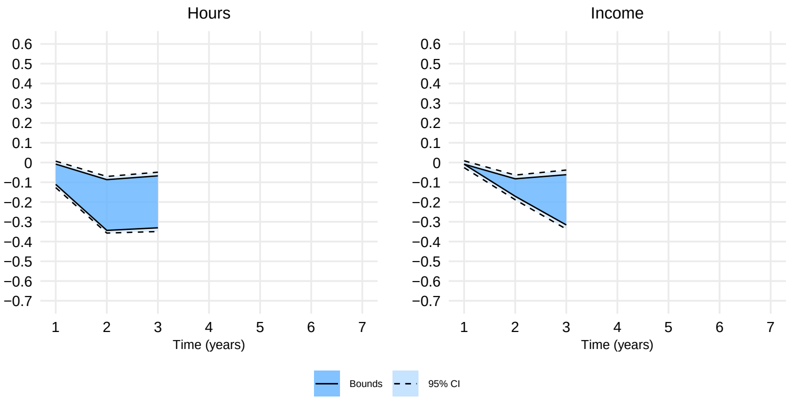


Figure 1: Bounds - short run

Baseline Lee bounds Absolute effects

Results: Bounds

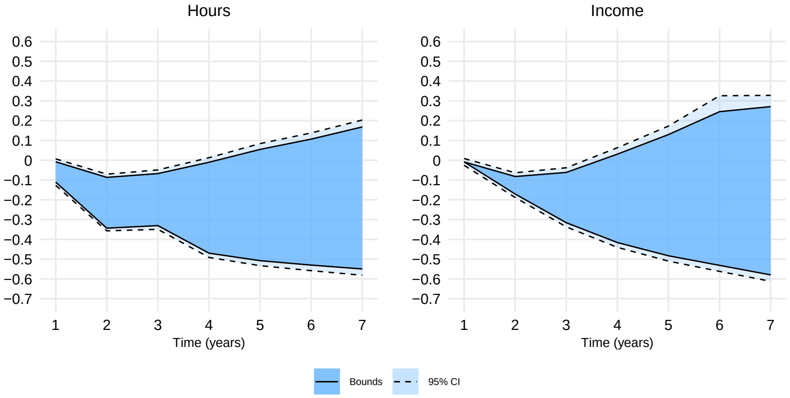


Figure 2: Bounds - medium run

Baseline Lee bounds Absolute effects

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

Bounds with Monotonicity

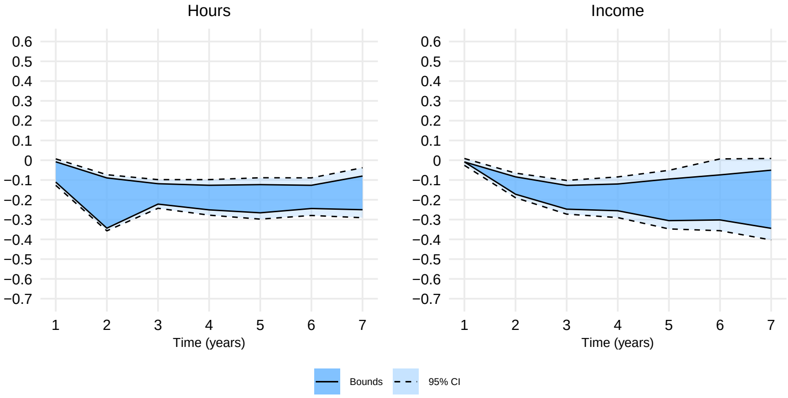


Figure 3: Bounds for percent effects

Absolute How wide?

Monotone Bounds - Gender Inequality

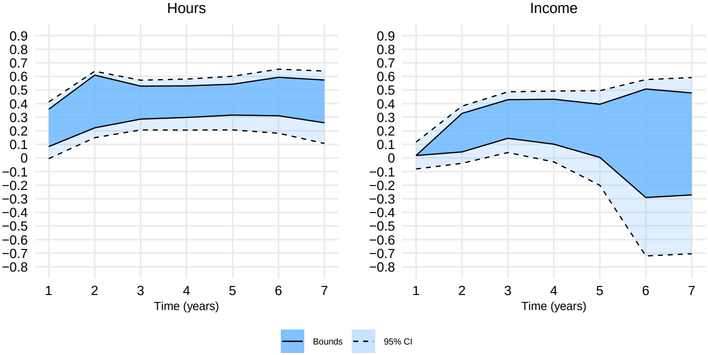


Figure 4: Share of gender inequality caused by parenthood

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
- 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

- Method for evaluating the career cost of children robust to selective fertility and dynamic effects
  - Applicable to settings with sequential treatment assignment and non-compliance
- Application to Dutch data:
  - Sizable career impacts of motherhood
  - Parenthood causes 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

Related Literature

Gender inequality in labor market outcomes.

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

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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

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

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

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

ToC

Identification Intuition (cont.)

ToC

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

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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

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

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

Back

ToC

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)

ToC

Assisted Conception Procedures

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 use the moment embryos/sperm are transferred into the uterus

Is success as-good-as-random? Background

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 Background

Randomness in IUI and IVF

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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

ToC

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.

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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.

Predicted Success Prob. per Treatment

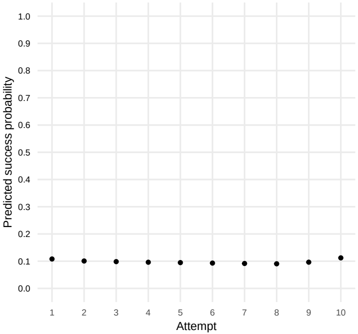

Figure 5: Predicted success probability holding X fixed at first attempt average

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Attempts

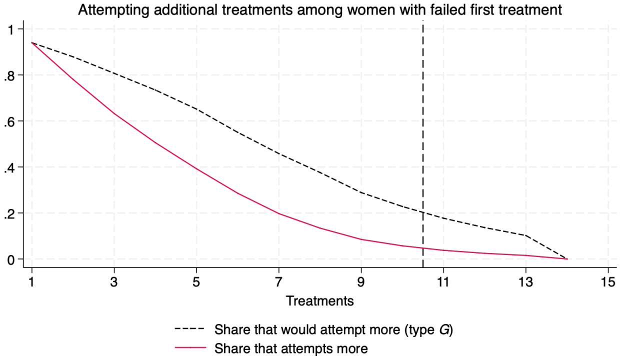

Figure 6: Number of treatments and type

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Non-treatment Conception by Type

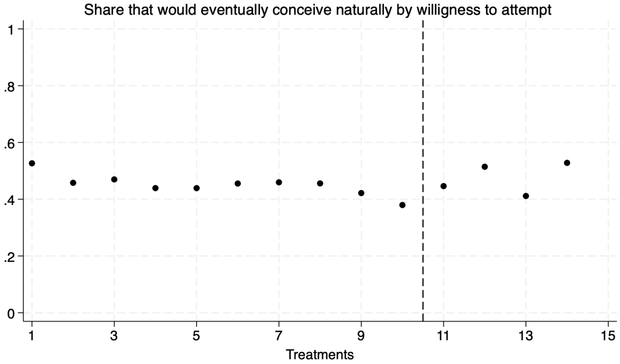

Figure 7: Conceiving naturally and willingness to attempt

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Trimming shares

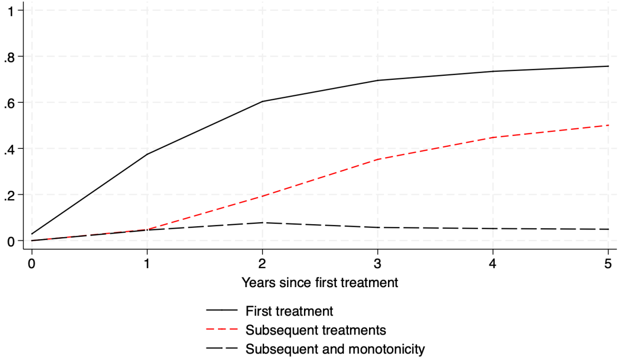

Figure 8: Trimming share under different information

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Correction Term

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

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Bounds: Absolute

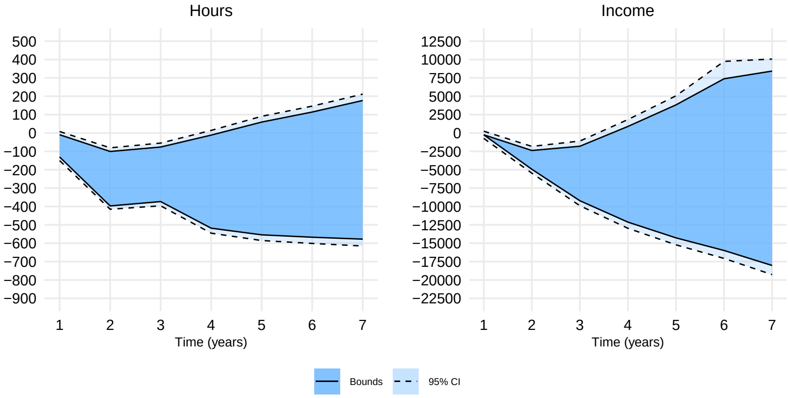

Figure 9: Bounds effects

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Bounds: Hours - Comparison to Baseline Lee Bounds

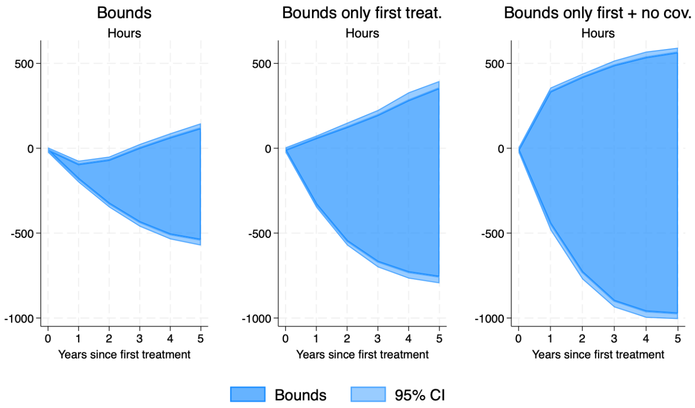

Figure 10: Comparison with baseline Lee: hours

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Bounds: Income - Comparison to Baseline Lee Bounds

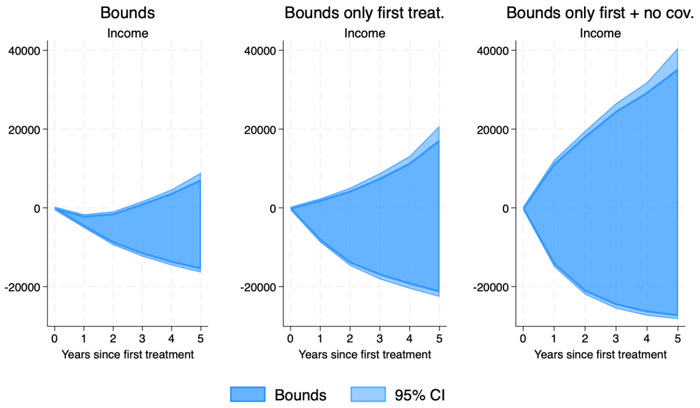

Figure 11: Comparison with baseline Lee: income

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Monotonicity (cont.)

Is monotonicity realistic?

Monotonicity (cont.)

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- 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.

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ToC

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  - Stronger sufficient assumption: success cannot increase total (natural) births.
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  - Couples may realize they are fertile and try more.

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  - Couples may realize they are fertile and try more.
  - First child may "save the relationship" resulting in more attempts to conceive.

ToC

Monotonicity (cont.)

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  - 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.

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- This restricts which women among successfully treated could have remained childless had all treatment attempts failed.
- Narrower bounds.

Intuition Back

ToC

Monotonicity: Intuition (1)

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

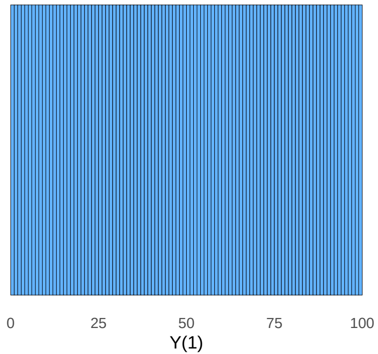

Figure 12: Distribution of potential motherhood outcomes

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Monotonicity: Intuition (2)

Without monotonicity: 20 with highest/lowest outcomes:

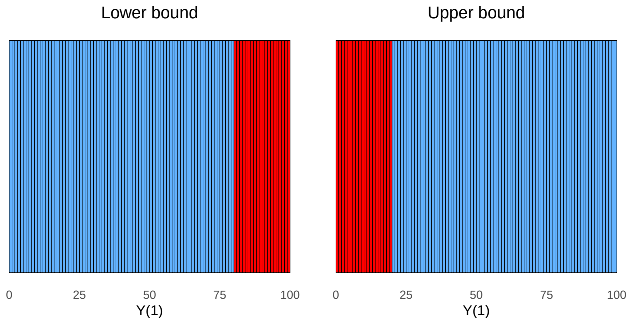

Figure 13: Distribution of potential motherhood outcomes

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Monotonicity: Intuition (3)

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

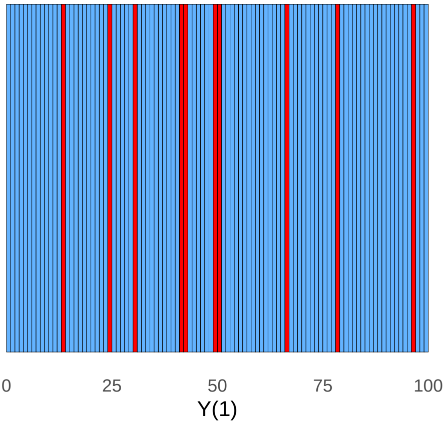

Figure 14: Distribution of potential motherhood outcomes

Monotonicity: Intuition (4)

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

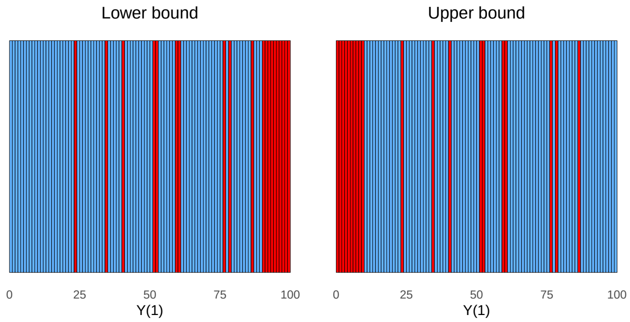

Figure 15: Distribution of potential motherhood outcomes

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Monotonicity: Intuition (5)

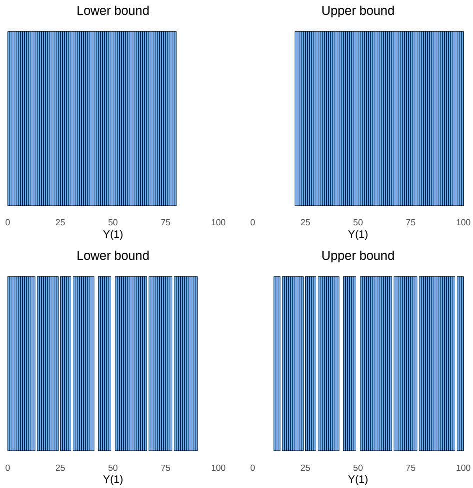

Figure 16: Distribution of potential motherhood outcomes

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Monotone Bounds: Absolute

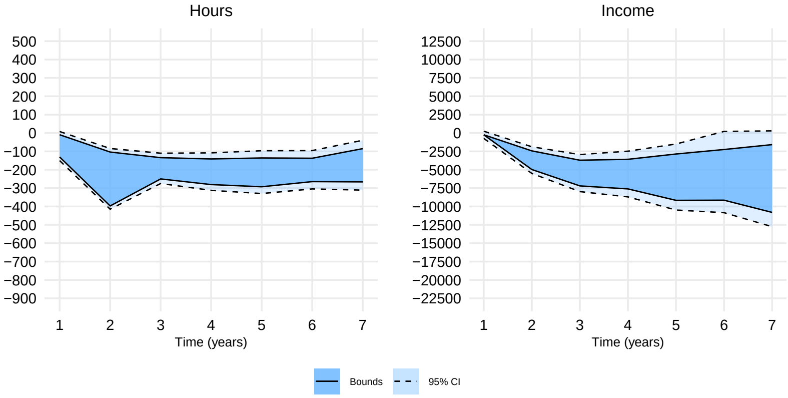

Figure 17: Monotone bounds: absolute terms

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ToC

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

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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

ToC

Monotone Bounds: Women who Remain Childless

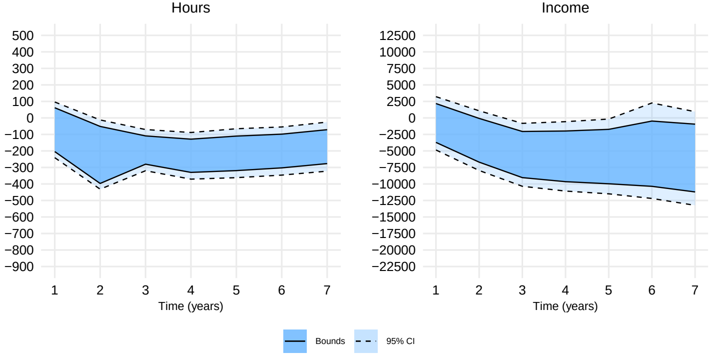

Figure 18: Monotone bounds using final status

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Event Study: Population vs IUI Sample

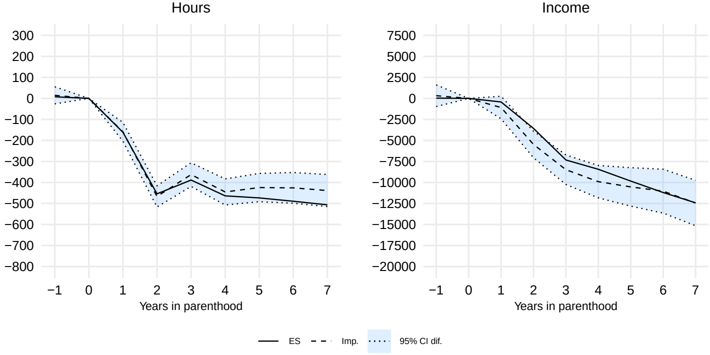

Figure 19: ES for population and women with first IUI success

Back (extensions) Back (intro)

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Imputing Population Motherhood Outcomes Using IUI Sample

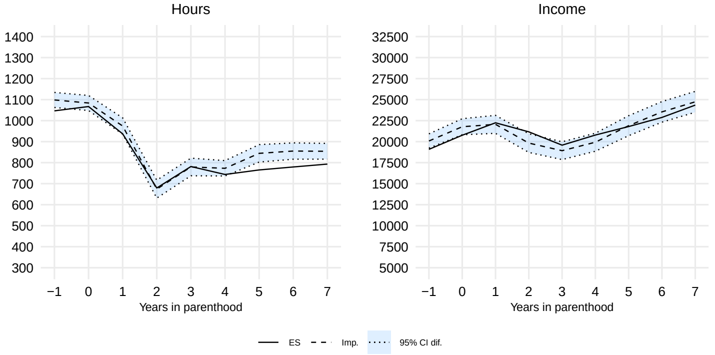

Figure 20: Population Outcomes vs IUI-imputation (age & education)

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Imputing Population Childless Outcomes Using IUI Sample

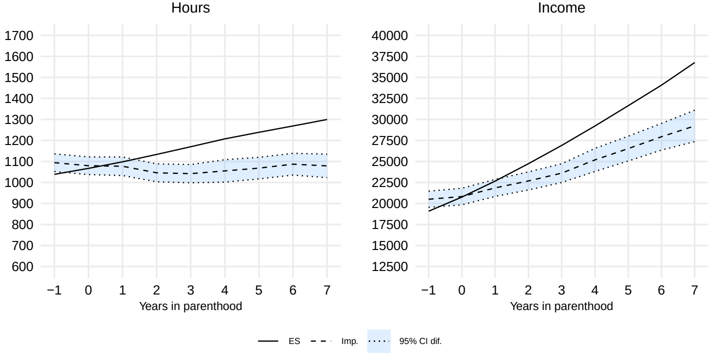

Figure 21: Population Outcomes vs IUI-imputation (age & education)

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Event Study vs IUI-imputation for Population

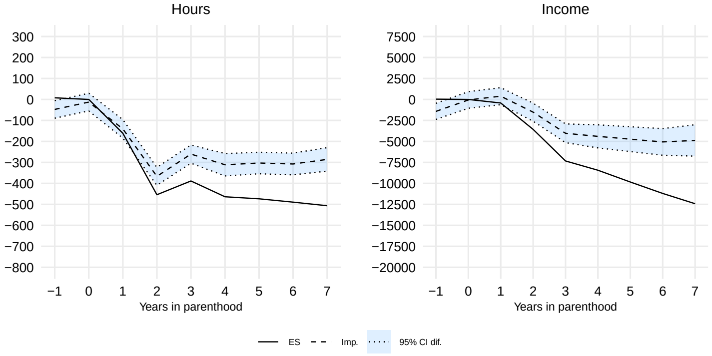

Figure 22: Event study vs IUI-imputation for population (age & education)

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Event Study vs IUI-imputation: Inequality

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

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Event Study vs IUI-imputation: Inequality

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

ToC

Event Study vs IUI-imputation: Inequality

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

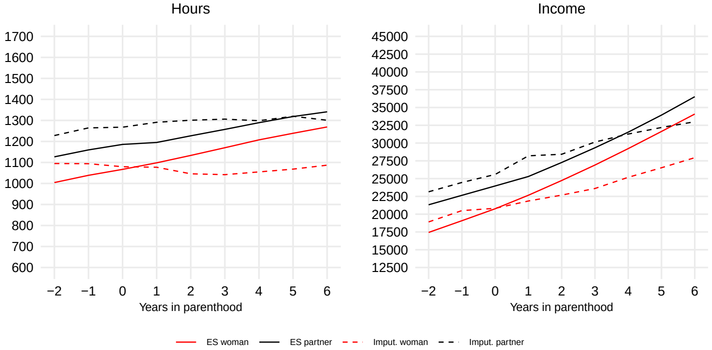

Figure 23: Event study vs IUI-imputation for population gaps (age & education), partner outcomes shifted 3 years

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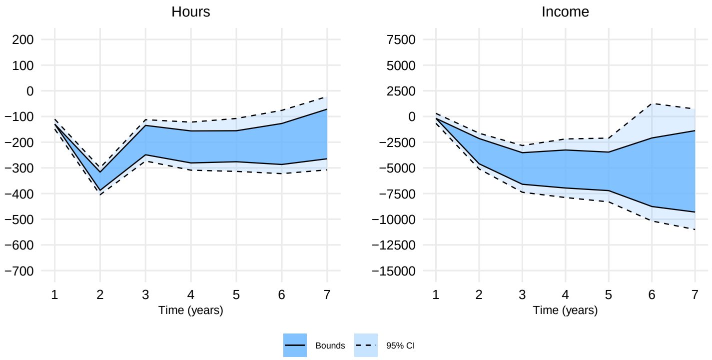
Simple estimator



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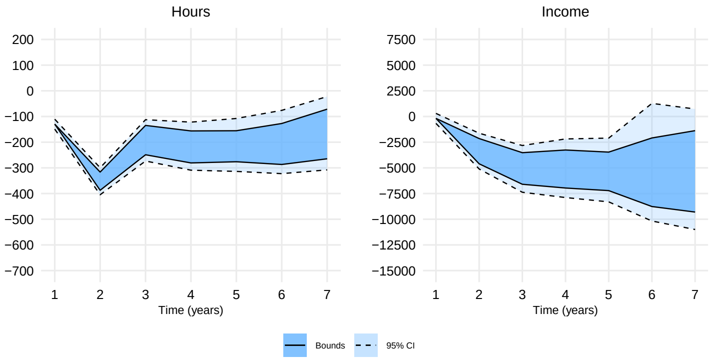
Simple estimator



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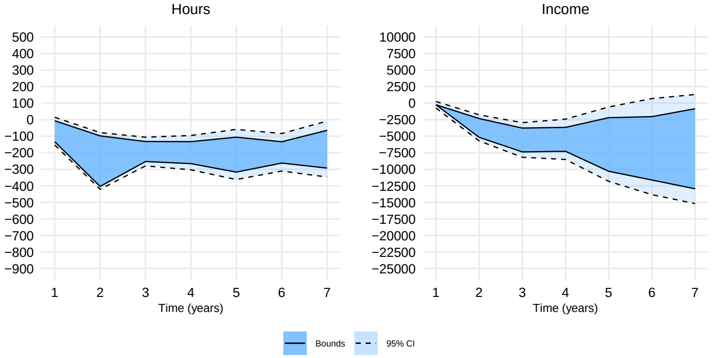
Relaxing Monotonicity Direction



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Heterogeneity by Covariates

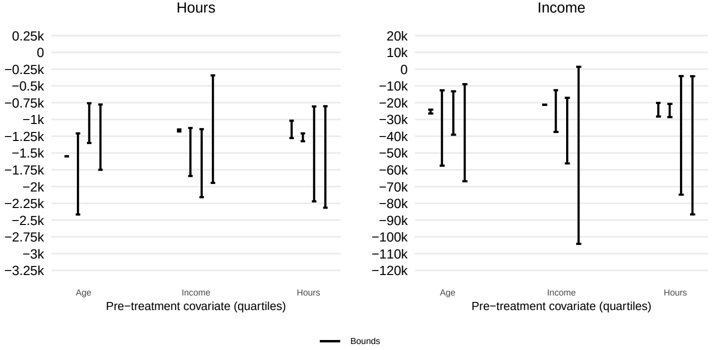

Figure 24: Cumulative outcomes after 6 years, pre-treatment covariates

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Heterogeneity by Willingness to Undergo Procedures

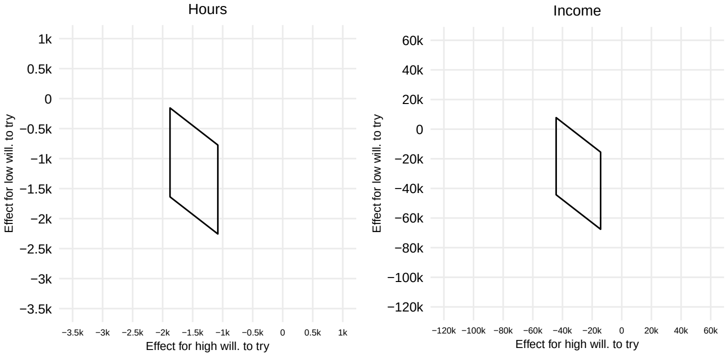

Figure 25: Cumulative outcomes 6 years after, G above or below 6

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Monotone Bounds: Excluding Depression

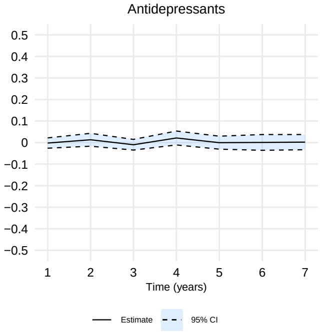

Figure 26: Sequential-IV estimates for effect on antidepressant take-up

Back (extensions) Back (model)

ToC

Monotone Bounds: Excluding Depressed

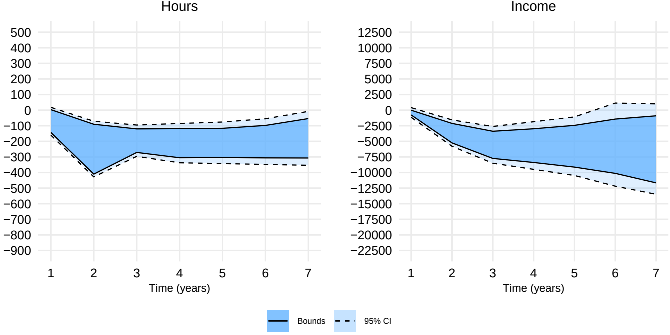

Figure 27: Monotone bounds for women who would not start antidepressants if they were to remain childless

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)

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Monotone Bounds: Assuming Maximum Leave

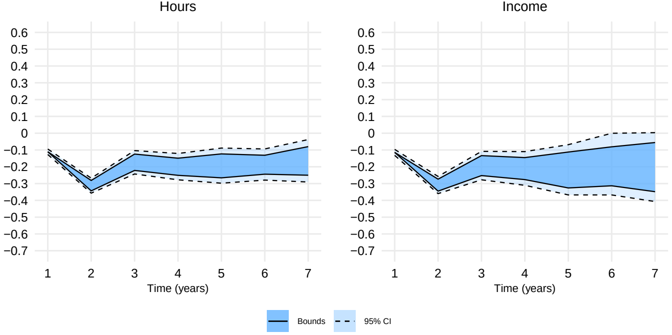

Figure 28: Monotone bounds scaling outcomes in years with childbirth by max. leave fraction

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Monotone Bounds: Correcting for Partner's age

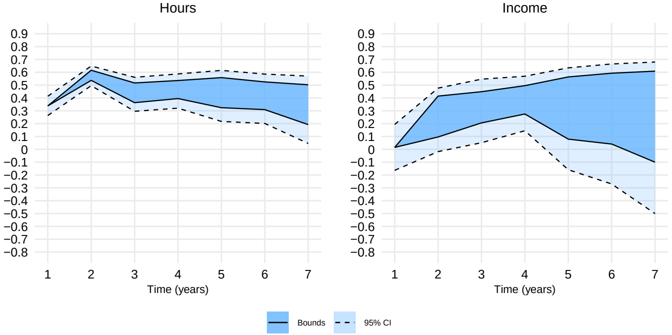

Figure 29: Monotone bounds using male income at same age as female

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Monotone Bounds: Fatherhood Penalty

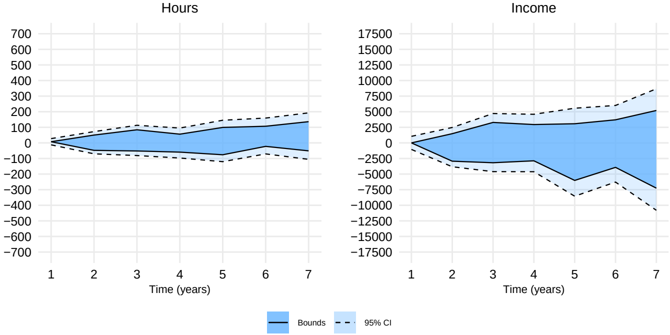

Figure 30: Monotone bounds for partners

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Monotone Bounds: Fatherhood Penalty in Percent

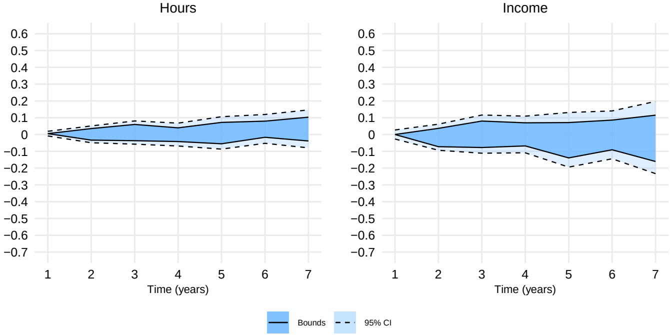

Figure 31: Monotone bounds for partners in percent

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Monotone Bounds: Explaining Gender Inequality

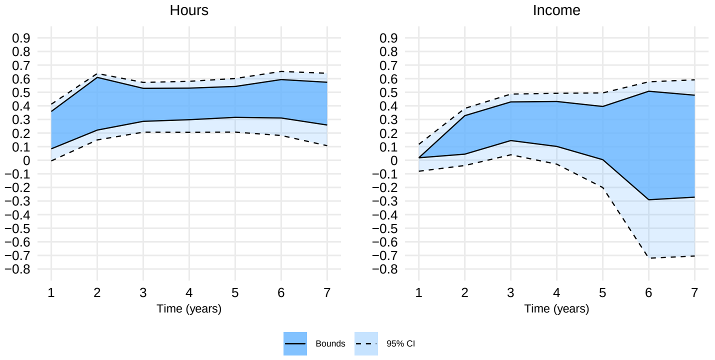

Figure 32: Share of gender inequality explained by parenthood

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Are Bounds Less Informative?

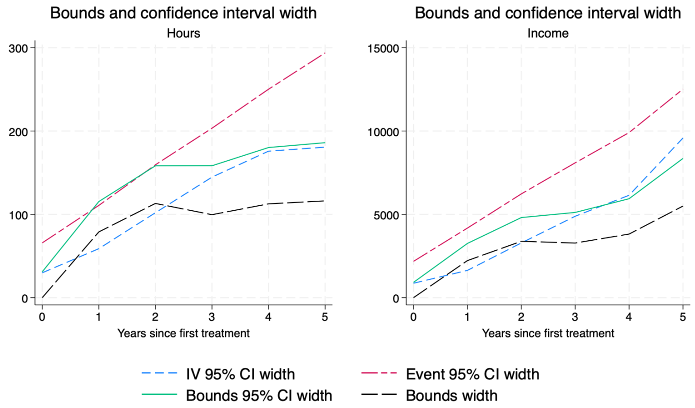

Figure 33: Confidence intervals for different methods

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Naive Comparison

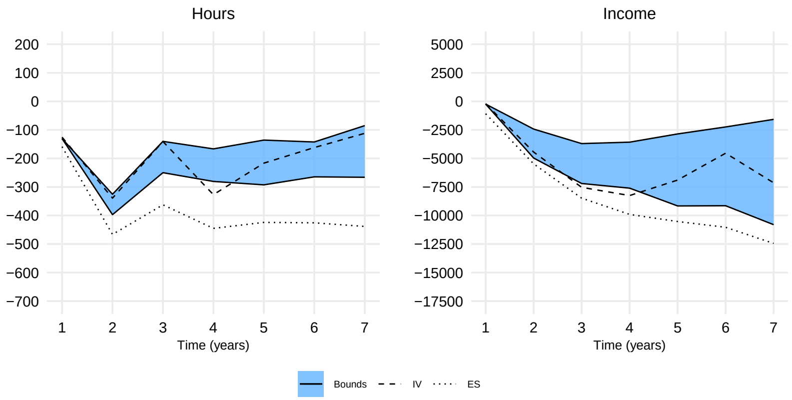

Figure 34: Estimates based on different methods

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

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Monotone Bounds and IV

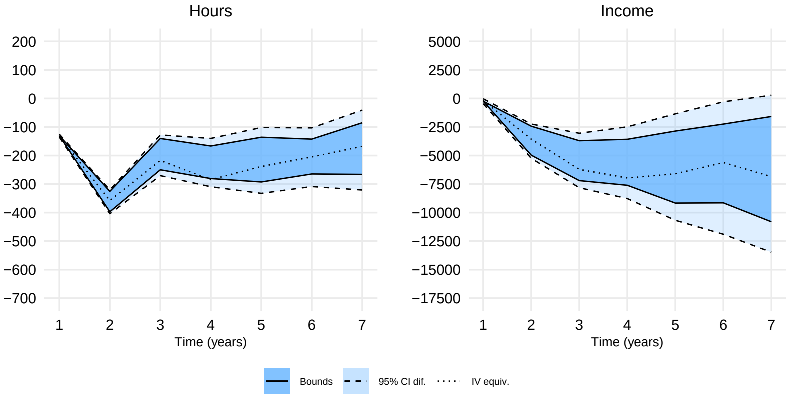

Figure 35: Bounds and IV equivalent for the same population

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Placebo Event

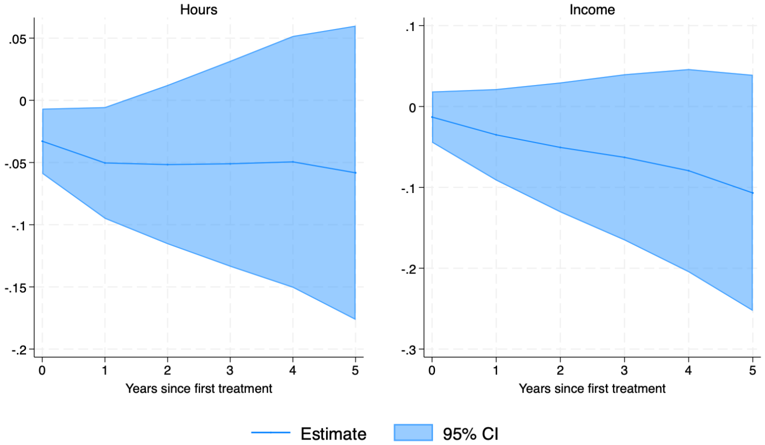

Figure 36: Placebo event study

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Placebo as causal

Inequality treating ES bias as causal

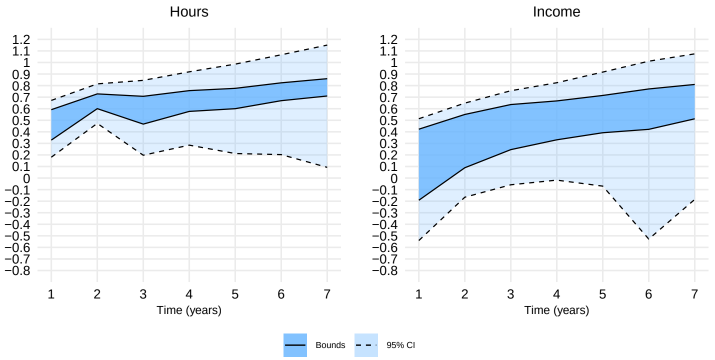

Figure 37: Placebo effects as share of bounds for the same population

Two possible interpretations:

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

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Yearly effect of Delaying Motherhood

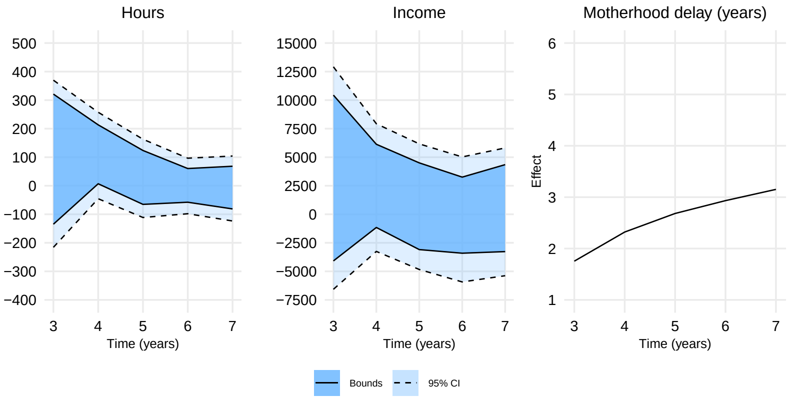

Figure 38: Effect of delaying relative to motherhood at first attempt

Opposite of what is frequently assumed!

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Cumulative effect of Delaying Motherhood

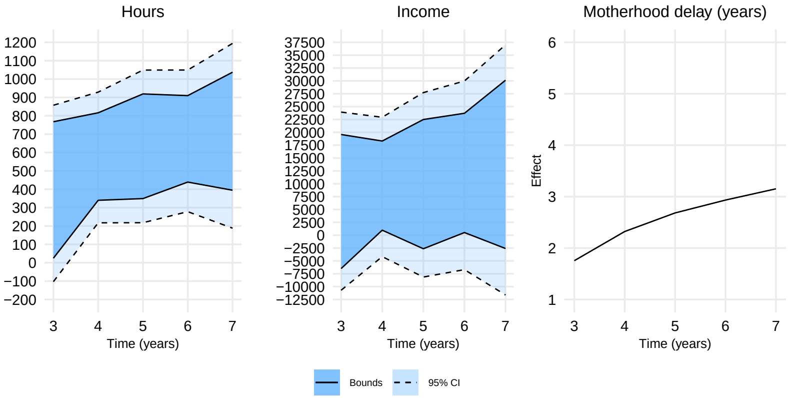

Figure 39: Effect of delaying relative to motherhood at first attempt

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Monotone Bounds: Women who Remain Childless

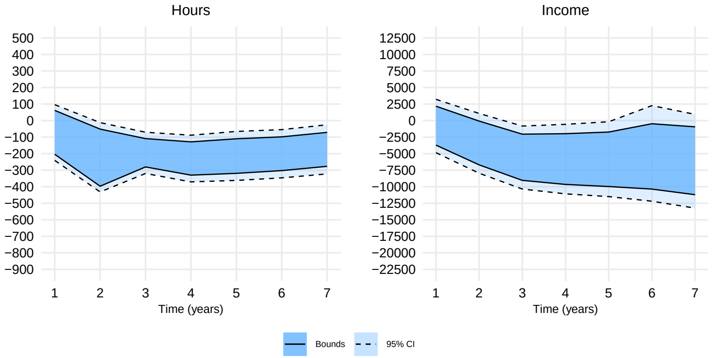

Figure 40: Monotone bounds using final status

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Relaxing Monotonicity to Partnered Women

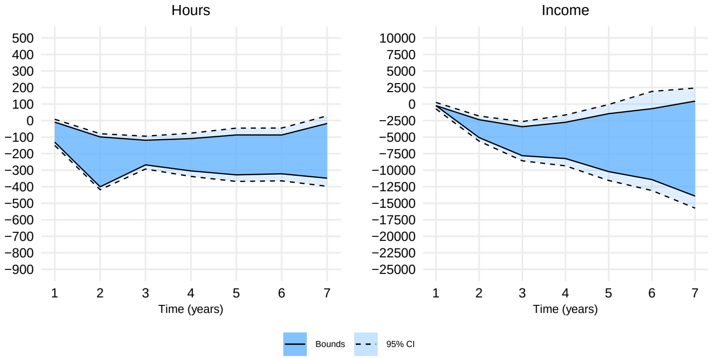

Figure 41: Monotone bounds using women who stay partnered

Back (extensions) Back (monotonicity)

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Testing the Plug-in Approach

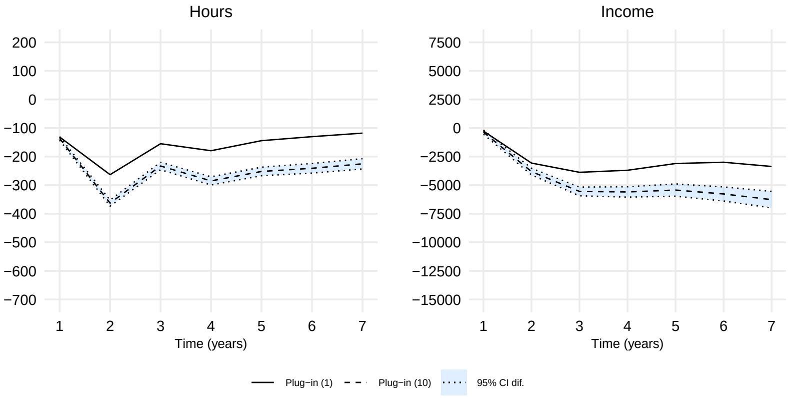

Figure 42: Plug-in estimators exploiting different number of treatments

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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.

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Estimated Bias and Placebo Event Study

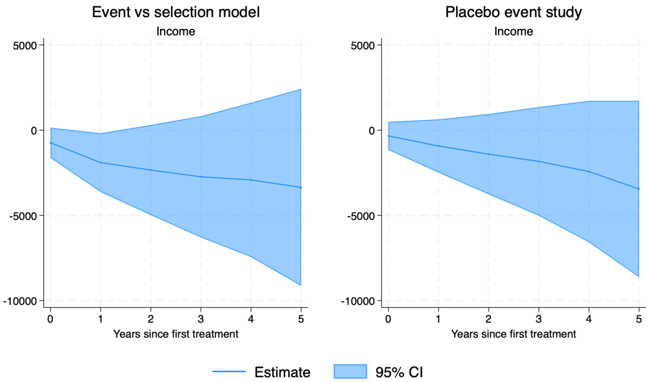

Figure 43: Difference between selection model estimate and event study estimate compared to placebo event study estimate

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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

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.

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.