Career Cost of Parenthood, Selective Fertility, and Dynamic Effects

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Motivation

Parenthood is often said to be the main cause of gender inequality in the labor market

- "Not surprisingly, **children** are the **main contributors** to women's labor supply changes." (Goldin, 2014)
- "...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 Has Proven Challenging

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

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)

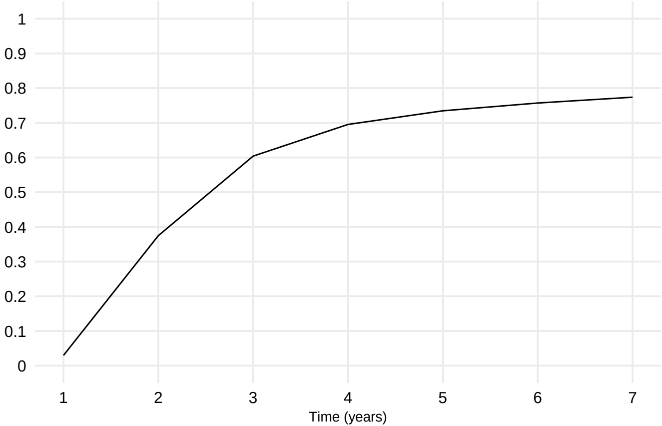
Event study (Kleven, Landais, & Søgaard, 2019):

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

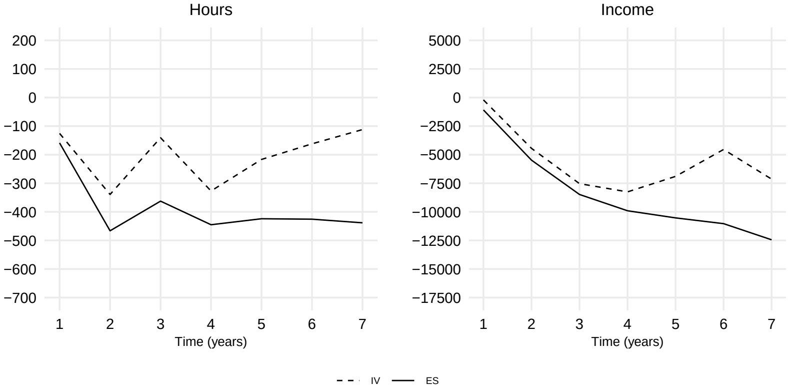
Motherhood After 1st Procedure Fails



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

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

IV vs ES



ES extern.

This Paper

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1. Novel approach using assisted conception procedures (ACPs) robust to endogenous timing and dynamic effects
   - IVF, IUI
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- 1^{st} success 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 assumption: (cond.) random ACP outcomes

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/embryo 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. Not represent. (only) due to unobs. het. in will. to try ACPs

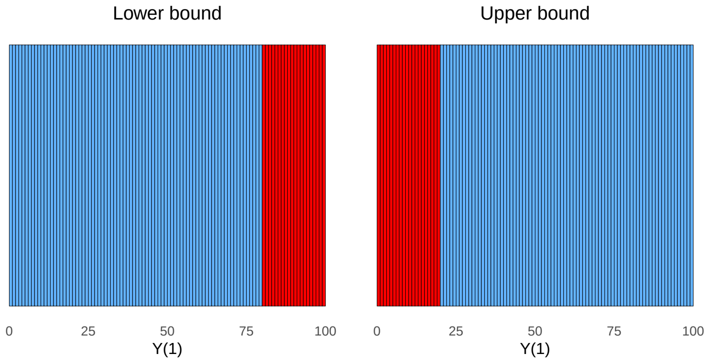
$$\Pr(C = 0|R = 1, W = w) = (1 - e)^W$$

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

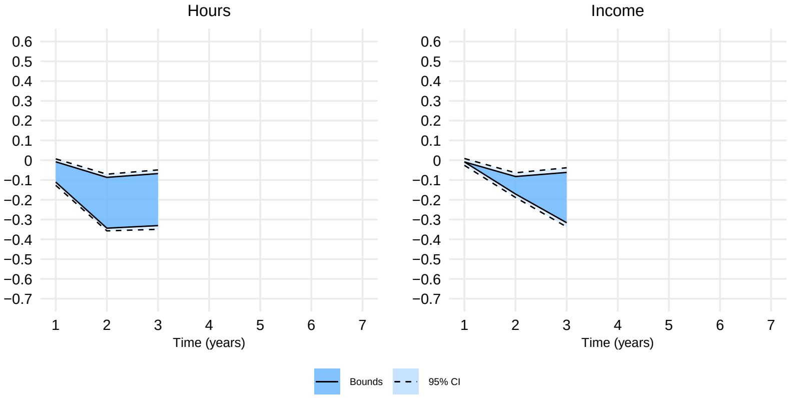


Figure 1: Bounds - short run

Baseline Lee bounds Absolute effects

Results: Bounds

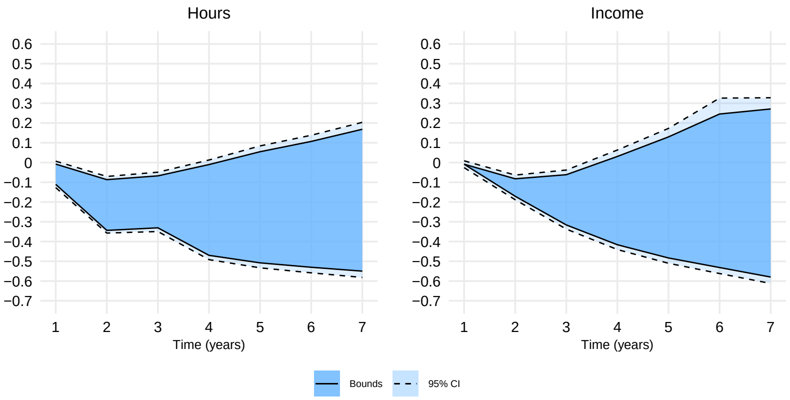


Figure 2: Bounds - medium run

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

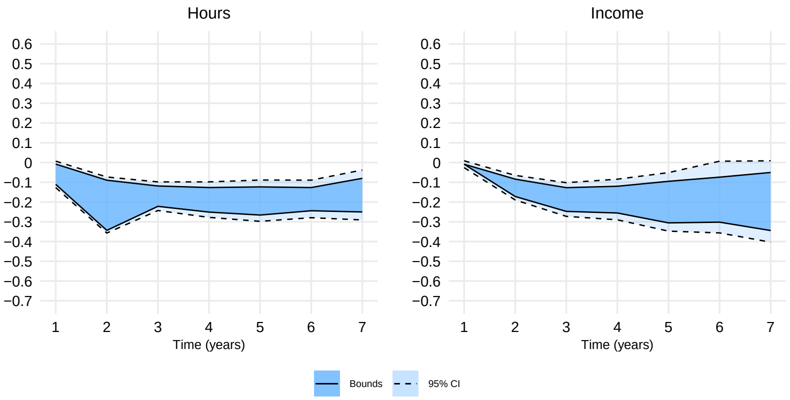


Figure 3: Bounds for percent effects

Absolute How wide?

Bounds with Monotonicity - Gender Inequality

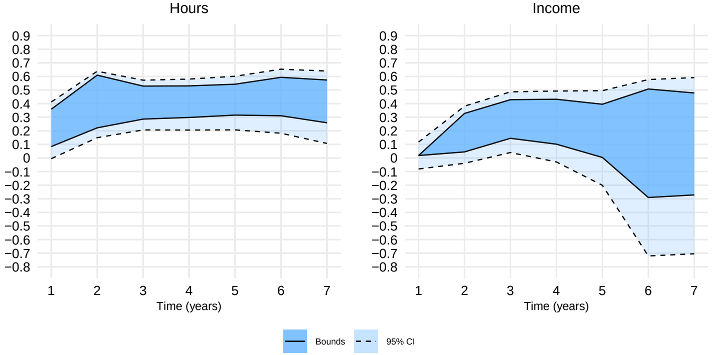


Figure 4: Share of gender inequality caused by parenthood

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 at most 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

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 than 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

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.

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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

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

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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.)

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Step 0:

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

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

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ToC

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

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

Treatment success is not completely random.

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ToC

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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.

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Predicted Success Prob. per Treatment

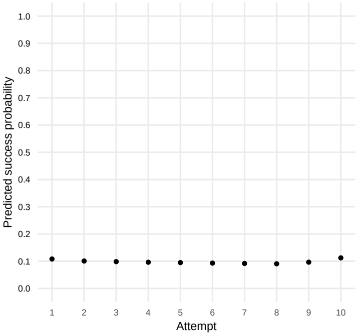

Figure 5: Predicted success probability holding X fixed at first attempt average

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Attempts

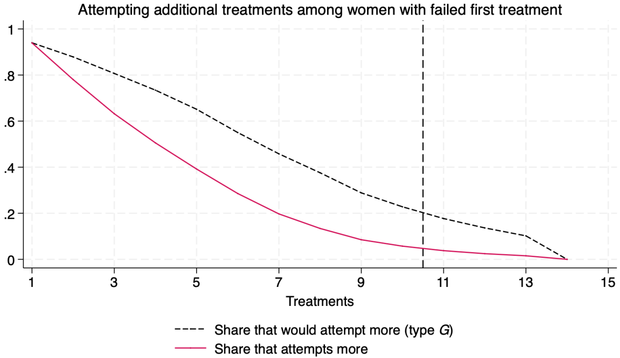

Figure 6: Number of treatments and type

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Non-treatment Conception by Type

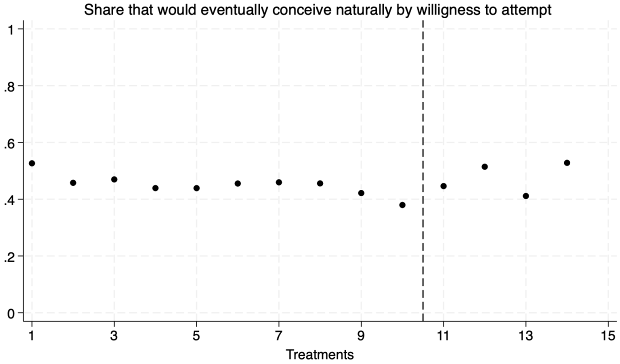

Figure 7: Conceiving naturally and willingness to attempt

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Trimming shares

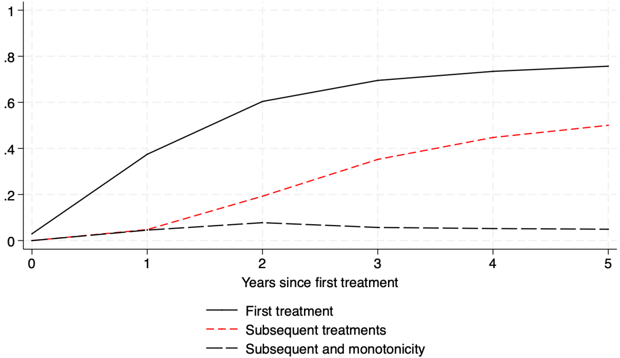

Figure 8: Trimming share under different information

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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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ToC

Bounds: Absolute

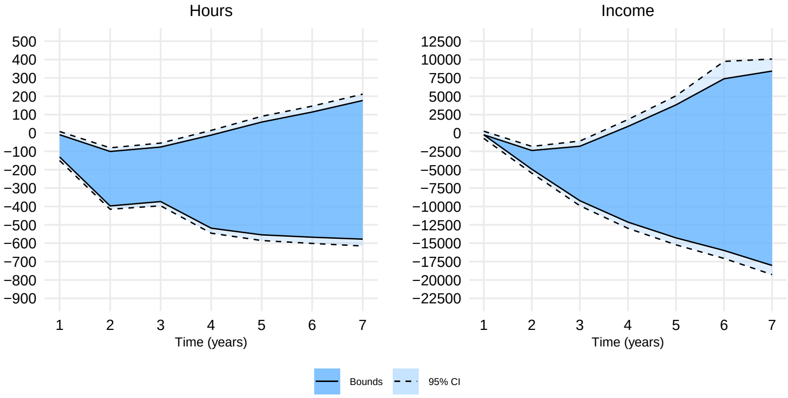

Figure 9: Bounds effects

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ToC

Bounds: Hours - Comparison to Baseline Lee Bounds

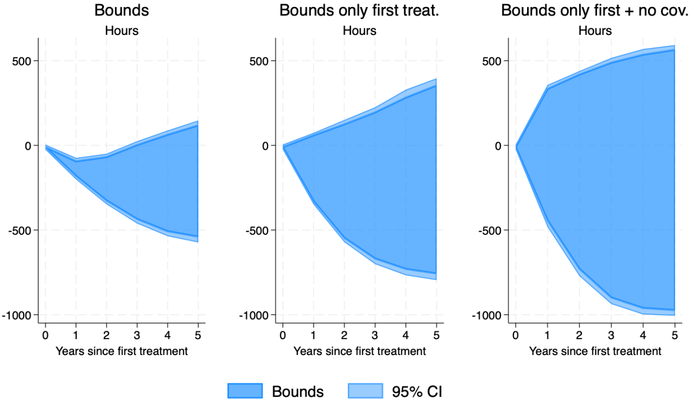

Figure 10: Comparison with baseline Lee: hours

Back

Bounds: Income - Comparison to Baseline Lee Bounds

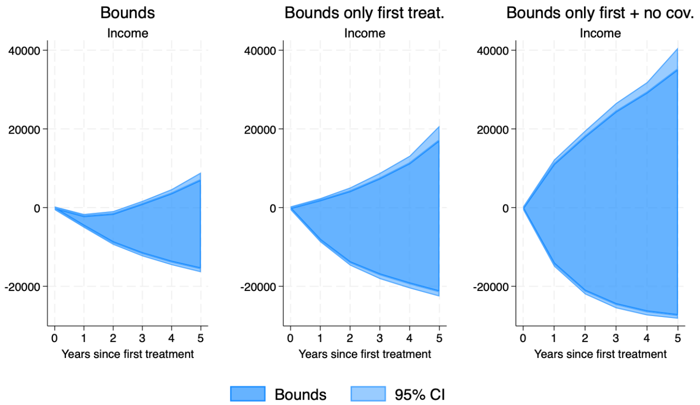

Figure 11: Comparison with baseline Lee: income

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Monotonicity (cont.)

Is monotonicity realistic?

Monotonicity (cont.)

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.

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  - 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.

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.

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.

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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:

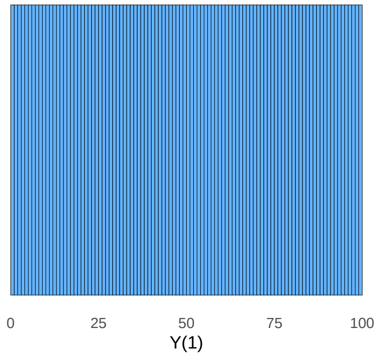

Figure 12: Distribution of potential motherhood outcomes

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ToC

Monotonicity: Intuition (2)

Without monotonicity: 20 with highest/lowest outcomes:

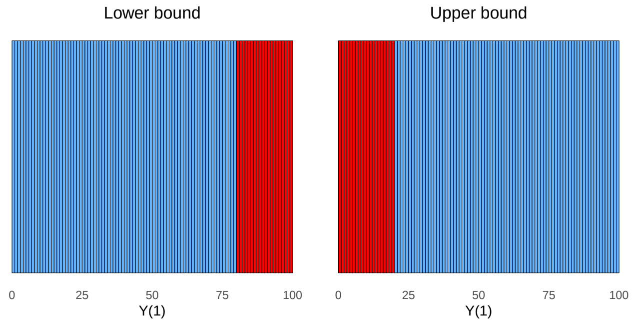

Figure 13: Distribution of potential motherhood outcomes

Back

Monotonicity: Intuition (3)

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

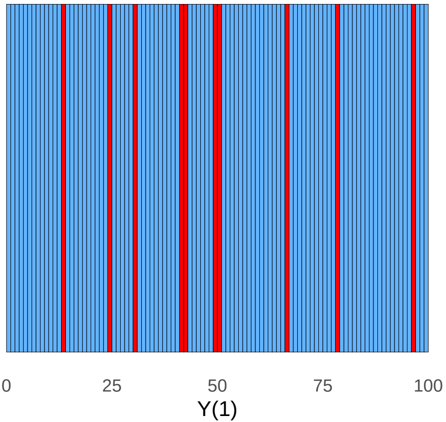

Figure 14: Distribution of potential motherhood outcomes

Monotonicity: Intuition (4)

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

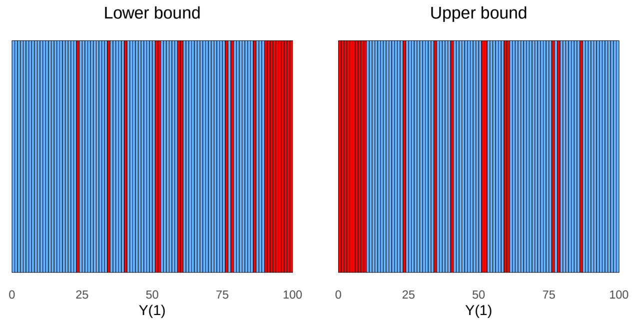

Figure 15: Distribution of potential motherhood outcomes

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ToC

Monotonicity: Intuition (5)

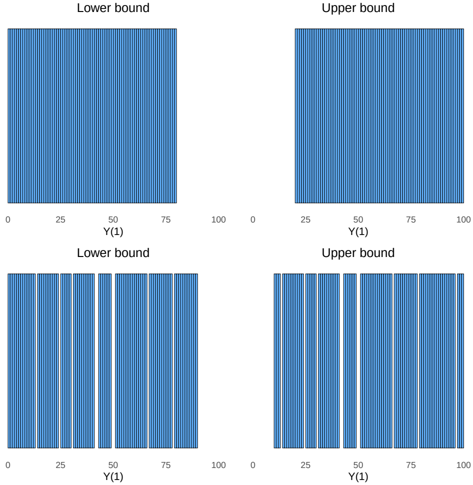

Figure 16: Distribution of potential motherhood outcomes

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ToC

Monotone Bounds: Absolute

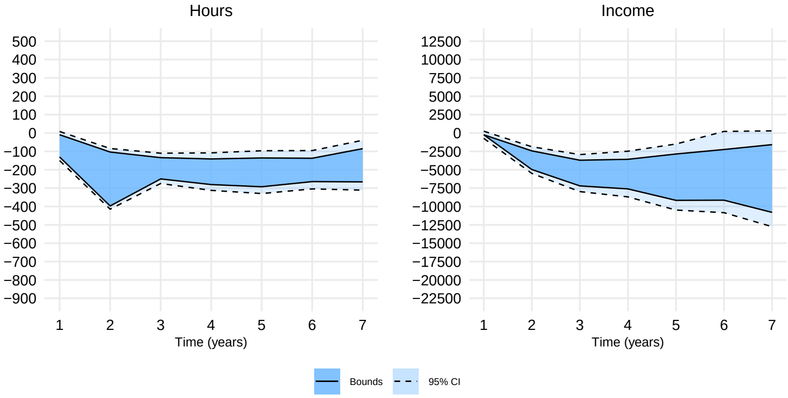

Figure 17: Monotone bounds: absolute terms

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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 estimators 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

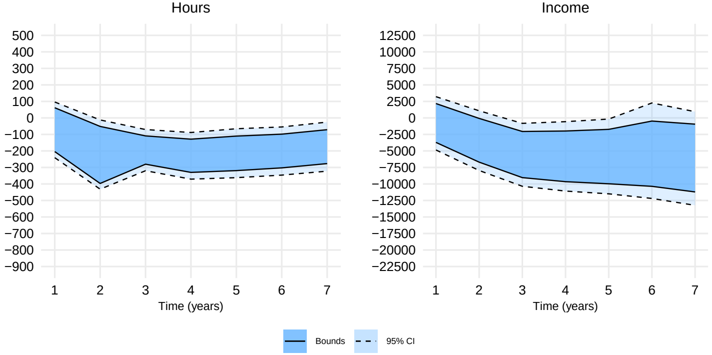

Figure 18: Monotone bounds using final status

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Event Study: Population vs IUI Sample

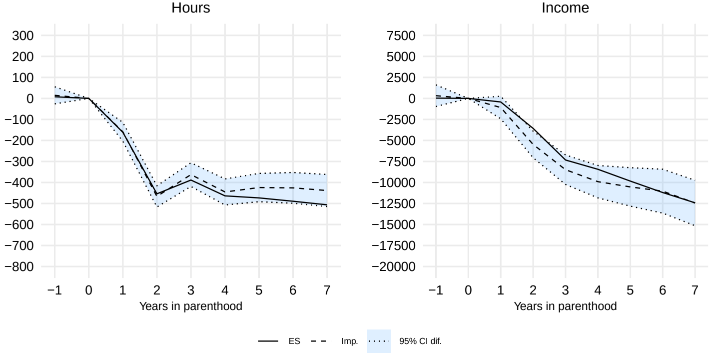

Figure 19: ES for population and women with first IUI success

Back (extensions) Back (intro)

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Imputing Population Motherhood Outcomes Using IUI Sample

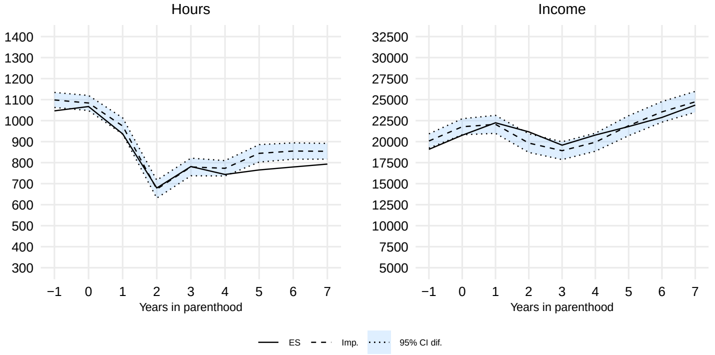

Figure 20: Population Outcomes vs IUI-imputation (age & education)

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Imputing Population Childless Outcomes Using IUI Sample

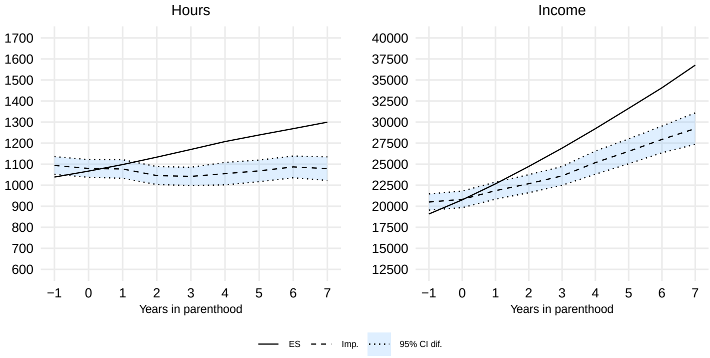

Figure 21: Population Outcomes vs IUI-imputation (age & education)

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Event Study vs IUI-imputation for Population

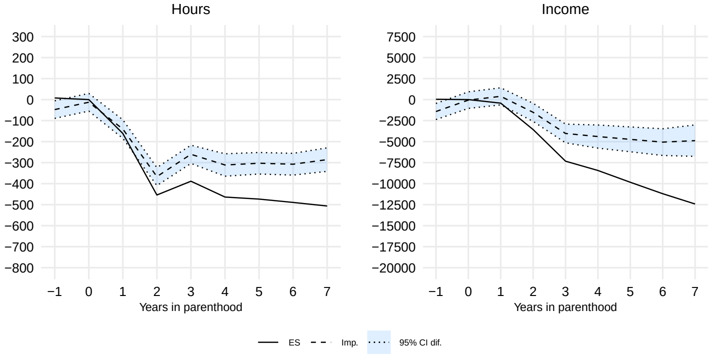

Figure 22: Event study vs IUI-imputation for population (age & education)

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Event Study vs IUI-imputation: Inequality

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

Event Study vs IUI-imputation: Inequality

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Event Study vs IUI-imputation: Inequality

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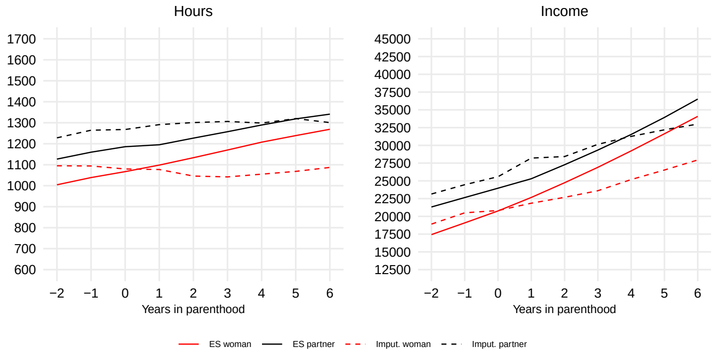
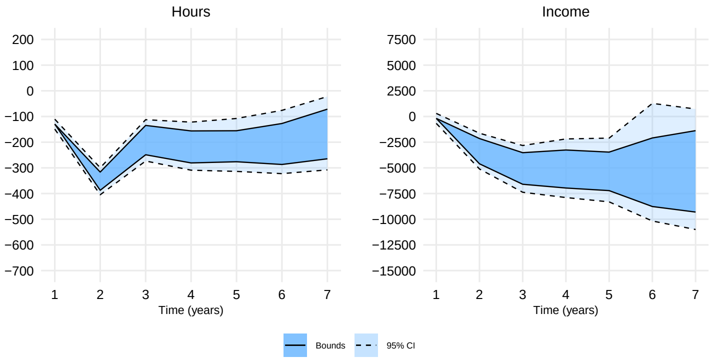


Figure 23: Event study vs IUI-imputation for population gaps (age & education), partner outcomes shifted 3 years

Simple estimator



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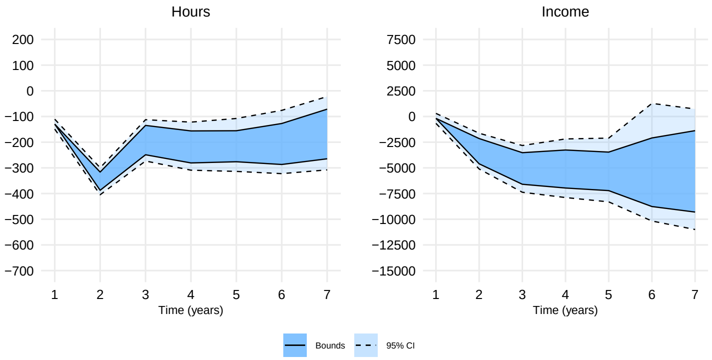
Simple estimator



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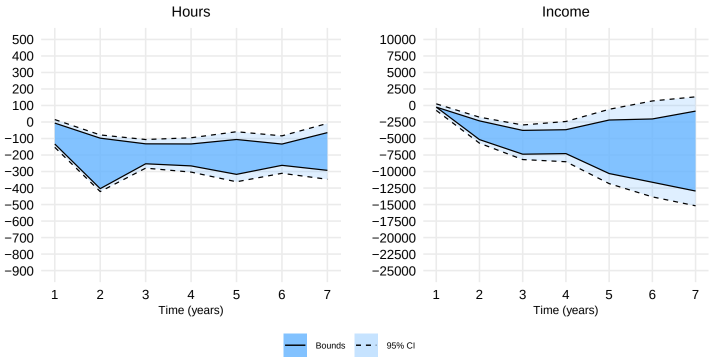
Relaxing Monotonicity Direction



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Heterogeneity by Covariates

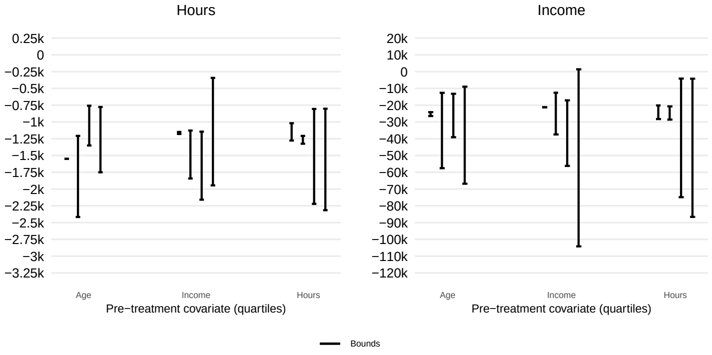

Figure 24: Cumulative outcomes after 6 years, pre-treatment covariates

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Heterogeneity by Willingness to Undergo Procedures

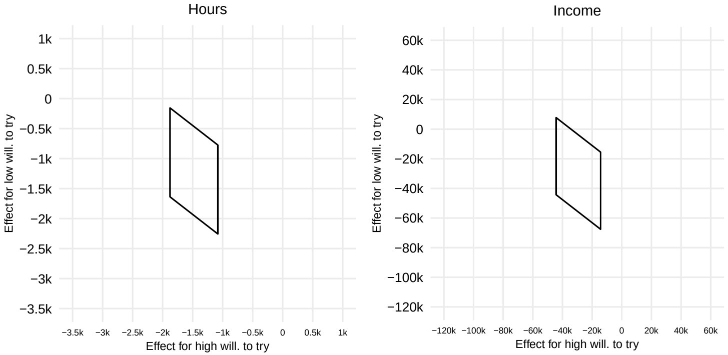

Figure 25: Cumulative outcomes 6 years after, G above or below 6

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Monotone Bounds: Excluding Depression

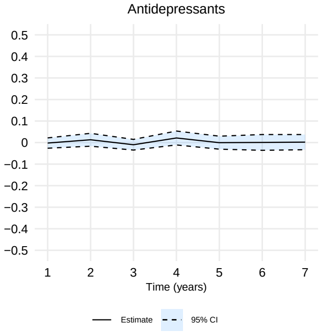

Figure 26: Sequential-IV estimates for effect on antidepressant take-up

Back (extensions) Back (model)

ToC

Monotone Bounds: Excluding Depressed

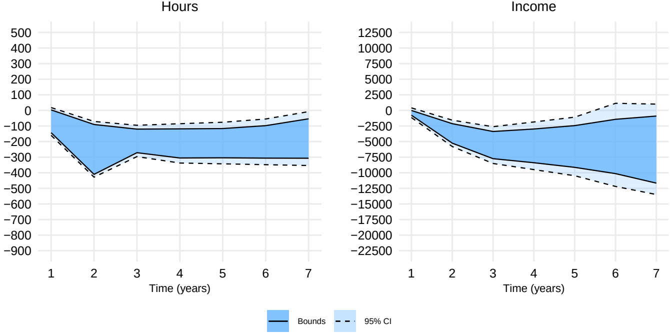

Figure 27: Monotone bounds for women who would not start antidepressants if they were to remain childless

Back (extensions) Back (model)

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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)

Monotone Bounds: Assuming Maximum Leave

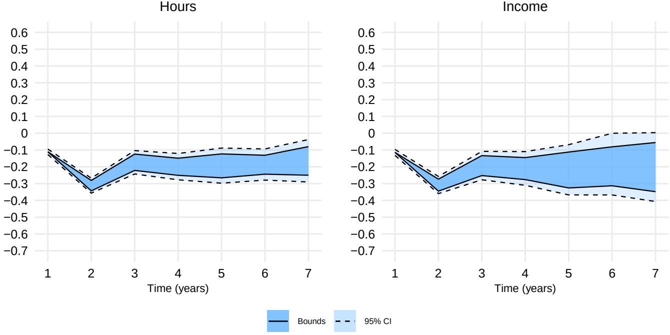

Figure 28: Monotone bounds scaling outcomes in years with childbirth by max. leave fraction

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Monotone Bounds: Correcting for Partner's age

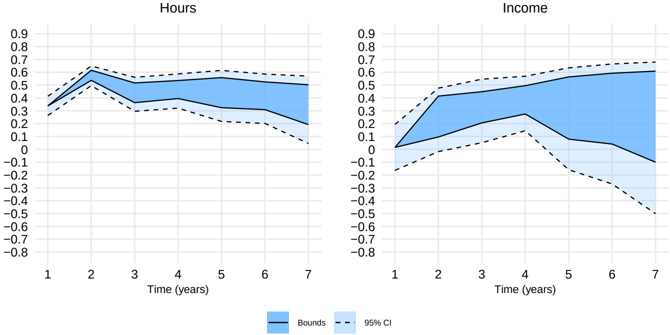

Figure 29: Monotone bounds using male income at same age as female

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Monotone Bounds: Fatherhood Penalty

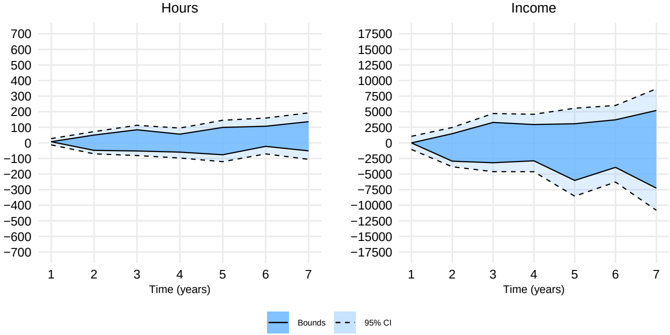

Figure 30: Monotone bounds for partners

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Monotone Bounds: Fatherhood Penalty in Percent

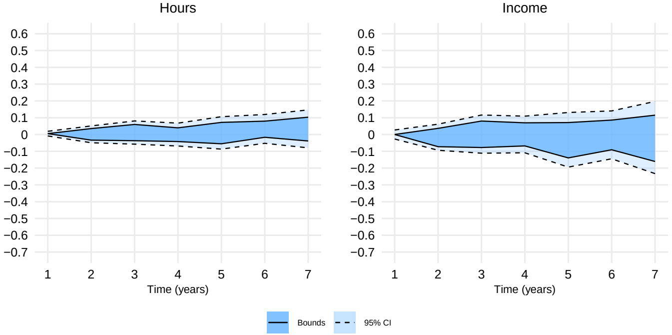

Figure 31: Monotone bounds for partners in percent

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Monotone Bounds: Explaining Gender Inequality

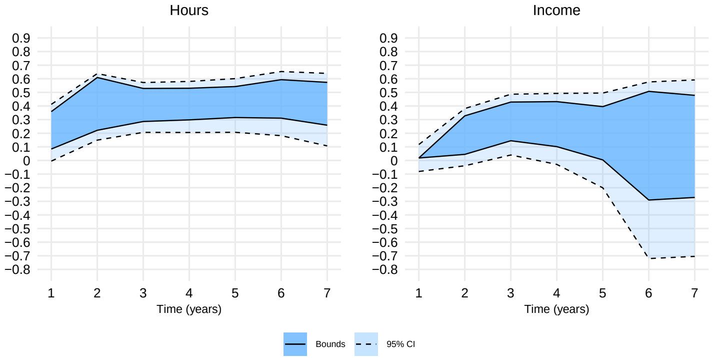

Figure 32: Share of gender inequality explained by parenthood

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Are Bounds Less Informative?

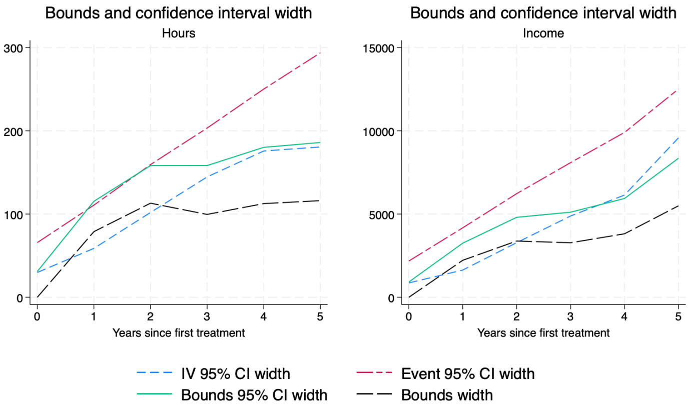

Figure 33: Confidence intervals for different methods

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Naive Comparison

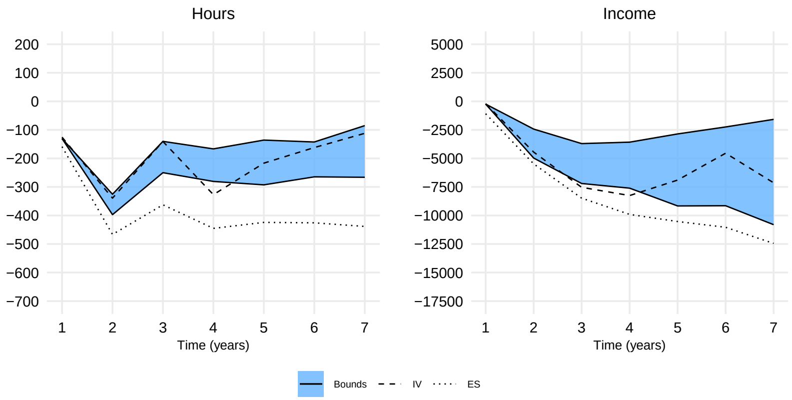

Figure 34: Estimates based on different methods

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

Monotone Bounds and IV

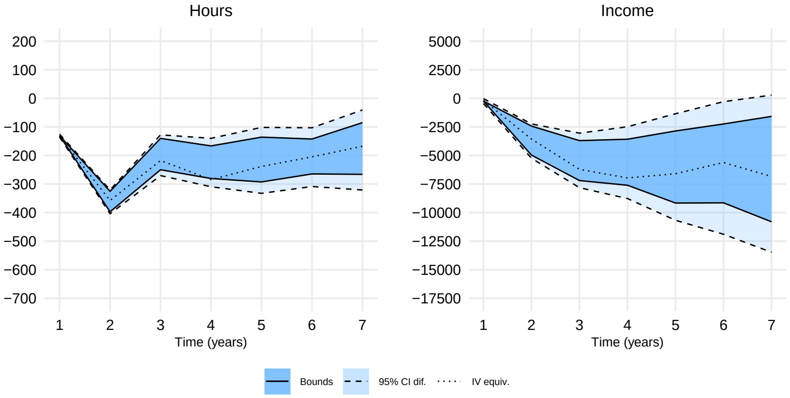

Figure 35: Bounds and IV equivalent for the same population

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Placebo Event

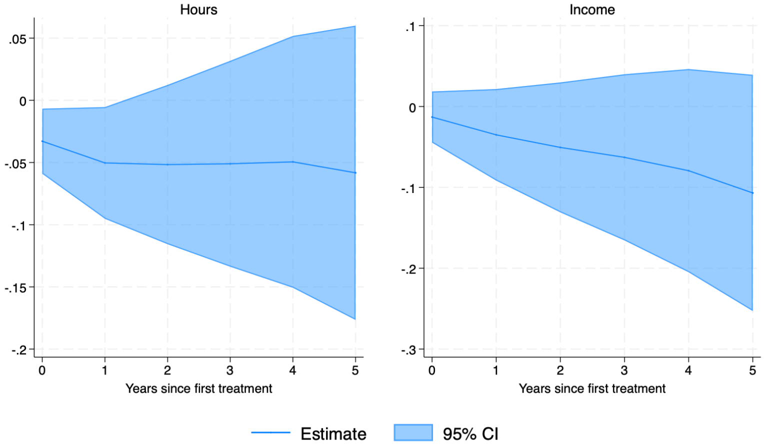

Figure 36: Placebo event study

ToC Back Placebo as causal

Inequality treating ES bias as causal

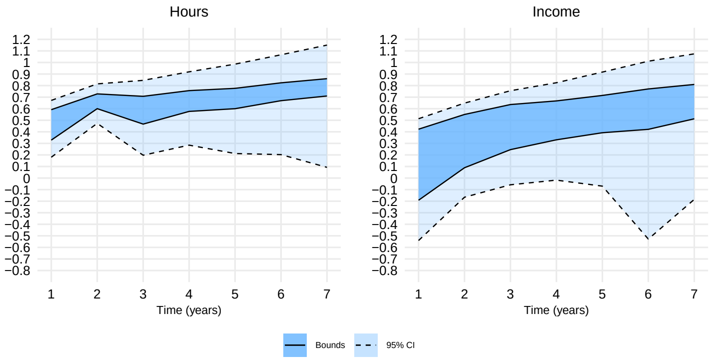

Figure 37: Placebo effects as share of bounds for the same population

Two possible interpretations:

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

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Yearly effect of Delaying Motherhood

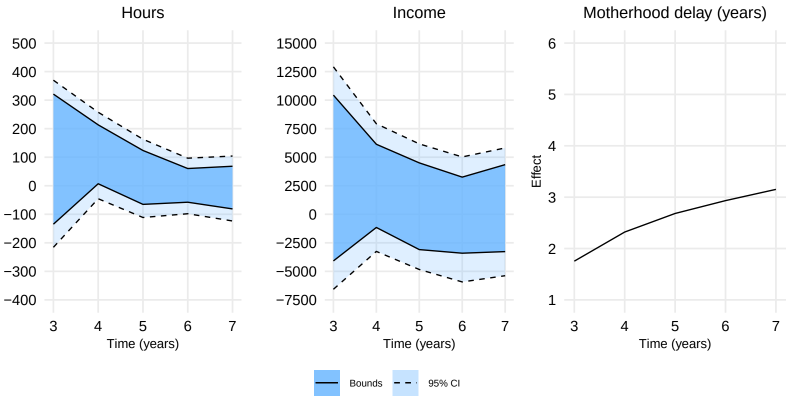

Figure 38: Effect of delaying relative to motherhood at first attempt

Opposite of what is frequently assumed!

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ToC

Cumulative effect of Delaying Motherhood

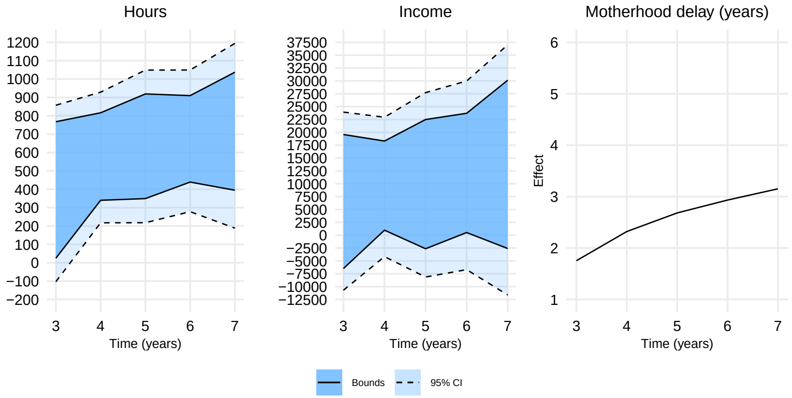

Figure 39: Effect of delaying relative to motherhood at first attempt

Back

Monotone Bounds: Women who Remain Childless

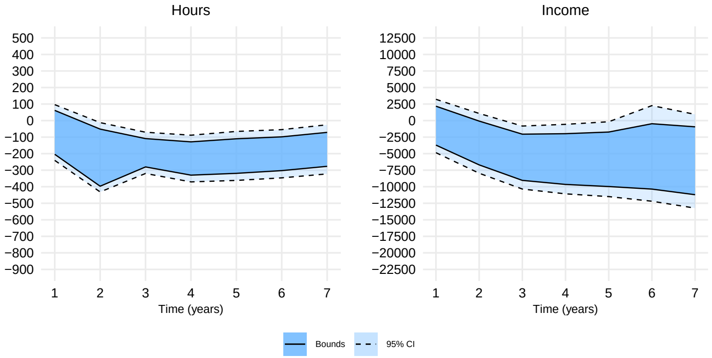

Figure 40: Monotone bounds using final status

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Relaxing Monotonicity to Partnered Women

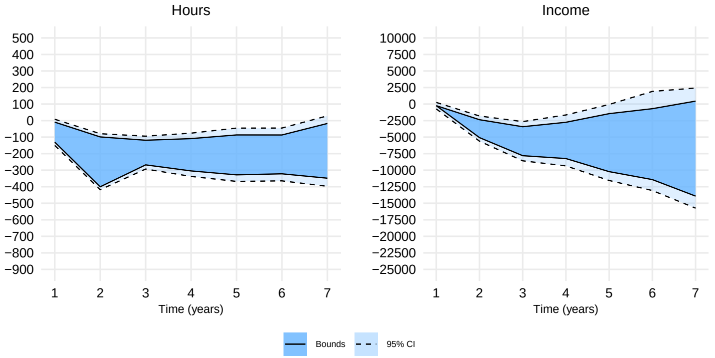

Figure 41: Monotone bounds using women who stay partnered

Back (extensions) Back (monotonicity)

ToC

Testing the Plug-in Approach

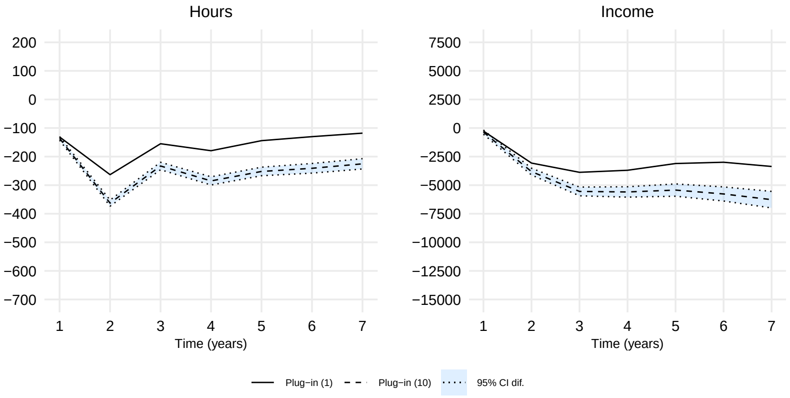

Figure 42: Plug-in estimators exploiting different number of treatments

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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

ToC

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

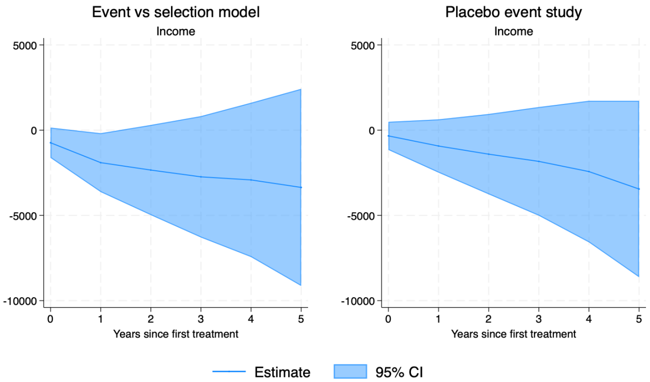

Figure 43: Difference between selection model estimate and event study estimate compared to placebo event study estimate

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