Parenthood Timing and Gender Inequality

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Motivation

Gender inequality in OECD labor markets emerges when individuals become parents

Quantifying the causal effect of parenthood is central to understanding and addressing gender inequity

Existing evidence is conflicting

At the core of the conflict are methodological challenges:

- 1. Parenthood (timing) may be selective: human capital, wealth, health, career prospects
- 2. Effects may depend on timing: age of children, career stage at childbirth

Existing methods cannot address both simultaneously

This Paper

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

- ▶ How would labor market outcomes of parents change if they did not have children
- 1. New approach to estimate treatment effects
 - Consider sequential quasi-experiments with dynamic non-compliance
- 2. Empirical evidence using novel administrative Dutch data
 - ► Focus on couples undergoing **intrauterine insemination**
- 3. Framework to assess the extent of selection and timing-dependent effects
 - Quantify bias in existing methods

Preview of Main Results

- ▶ Parenthood persistently reduces women's work hours and income
 - Yearly reductions between 9 and 24 percent
- ▶ Parenthood causes a large share, but far from all, of post-child gender inequality
 - ▶ Between 36 and 54 percent in work hours and up to 46 percent in income
- ▶ Both selection and dynamic effects are substantial
 - Sizable bias if either is unaccounted for

- 1. Existing quasi-experimental studies impose strong assumptions about timing
 - ► Hotz et al. (2005); Agüero & Marks (2008); Cristia (2008); Miller (2011); Lundborg et al. (2017); Bensnes et al. (2023); Gallen et al. (2023); Lundborg et al. (2024)

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- 4. Addressing selection and dynamic effects is a common challenge
 - Education programs with multiple admission cycles, assignment to judges, promotion tournaments

Method applicable to many other settings with sequential quasi-experiments

Baseline Instrumental Variable Setup

Addressing selection into parenthood requires a quasi-experiment: focus on women who undergo artificial insemination

- ▶ Outcome of the first procedure $Z_1 \in \{0,1\}$
- ▶ Parenthood indicator $D \in \{0, 1\}$
- ▶ Potential labor market outcomes $Y_{z_1}(d)$
- ▶ Effect of interest $Y_1(1) Y_0(0)$

Assuming first procedure success is random (unconfoundedness) and affects outcomes only via parenthood status (exclusion) enables identification

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However:

- ▶ 75% of women have children after the first procedure fails
- $ightharpoonup Z_1$ affects D, but also affects timing of parenthood
- **Exclusion** may be violated: $Y_1(1) \neq Y_0(1)$, leading to bias

Model

Women differ in two unobserved characteristics:

- "Willingness" to undergo ACPs, $W \in \{1, \dots, \overline{w}\}$
 - ▶ Would undergo W ACPs for the first child if all ACPs failed
- ▶ "Reliance" on ACPs, $R \in \{0, 1\}$
 - ightharpoonup No child if all ACPs fail, R=1

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Observables:

- \triangleright ACP j success indicator, Z_i , for procedures before having any children
- Number of realized ACPs:

$$A = \min (\{j : Z_j = 1\} \cup \{W\})$$

Parenthood indicator:

$$D = \max(Z_A, 1 - R)$$

Sequential Unconfoundedness

Assumption (Sequential Unconfoundedness)

$$(Y_1(1), Y_0(0), R, W) \perp \!\!\! \perp \!\!\! Z_j | A \geq j.$$

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

- ▶ The decision to undergo the procedure can be endogenous
- $ightharpoonup Y_1(1), Y_0(0), R$ and W can be related
- ▶ Main method relaxes to covariate-conditional version: age at procedure, technology

$$W=1 \ ext{(willing to try once)}$$

$$Z_1=1$$

$$Z_1 = 0$$

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

$$Z_1 = 1$$

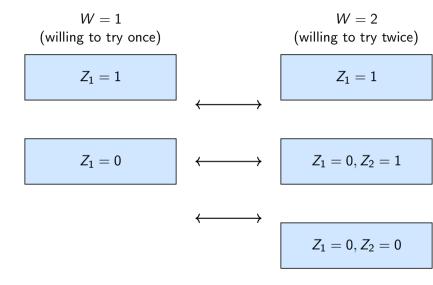
$$Z_1=0$$

$$W = 2$$
 (willing to try twice)

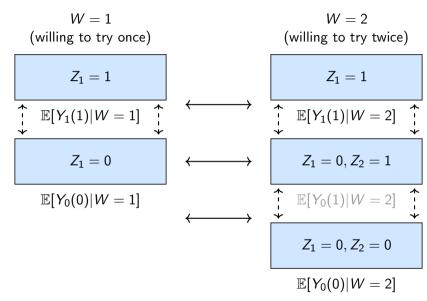
$$Z_1 = 1$$

$$Z_1=0,Z_2=1$$

$$Z_1=0,Z_2=0$$





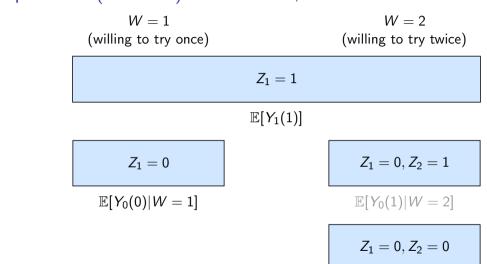


$$W=1$$
 (willing to try once) $W=2$ (willing to try twice) $Z_1=1$

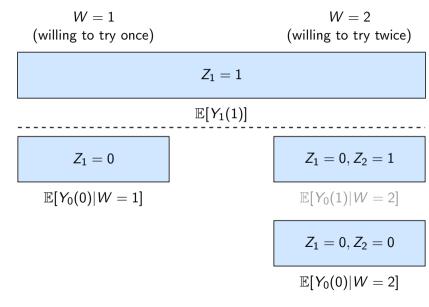
$$Z_1=0$$

$$Z_1=0,Z_2=1$$

$$Z_1=0,Z_2=0$$



$$\mathbb{E}[Y_0(0)|W=2]$$



$$W=1$$
 (willing to try once) $W=2$ (willing to try twice) $Z_1=1$ $\mathbb{E}[Y_1(1)]$ $Z_1=0$ $Z_1=$

$$R=1$$
 (no child if fail) $R=0$ (child if fail)

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$$Z_1=1$$

$$R=1$$
 (no child if fail)

$$R=0$$
 (child if fail)

$$Z_1=1$$

$$Z_1=0,D=0$$

$$Z_1=0,D=1$$

$$R=1$$
 (no child if fail)

$$R = 0$$
 (child if fail)

$$Z_1=1$$

Distribution of
$$Y_1(1)$$

$$Z_1=0,D=0$$

$$\mathbb{E}[Y_0(0)|R=1]$$

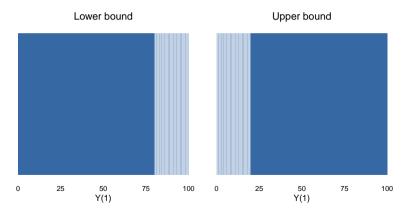
$$Z_1=0,D=1$$

$$\mathbb{E}[Y_0(1)|R=0]$$

$$Pr(R=1) =$$

Intuition: Motherhood Outcome $Y_1(1)$

- 1. Treated group is a representative 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 $\mathbb{E}[Y_1(1)|R=1]$



Technical Details

Formal identification

- ► Covariate-conditional sequential unconfoundedness: age and procedure type
- Combine the two steps in a semi-parametric moment equation

Using covariates to narrow the bounds

► The bounds are sharp

Inference complicated by trimming of the outcome distribution

- ▶ Build on a double/debiased machine learning approach by Semenova (2023)
- Construct orthogonal moment functions that are robust to first-stage nonparametric estimation errors in quantile and other nuisance functions

Background and Data

Assisted conception procedures

- ▶ In-vitro fertilization: invasive medical procedure, first 3 free
- Intrauterine insemination: direct sperm injection, minimally invasive, free

Dutch family policies and labor market similar to OECD average

▶ 16 weeks maternity + pregnancy leave, 1 week paternity leave

Data combining ACP medical records with tax records -

- Work hours and income include leave; results for hours corrected for uncertainty
- ▶ 15,523 cohabiting opposite-sex couples
- Balance: ACP success at each attempt uncorr. with past outcomes cond. on age

 Details Balance in 1st ACP first Balance in later ACPs Success and willingness Rep. samp.

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Bounds

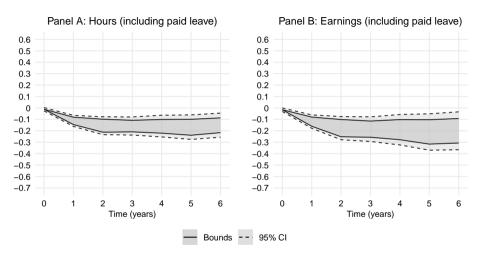


Figure 1: Bounds for Women

Bounds for Men

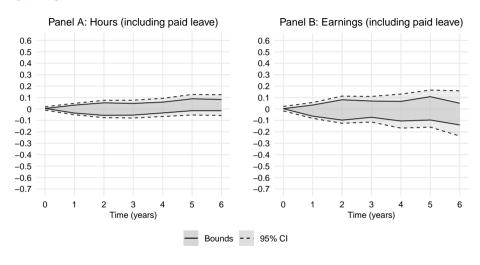


Figure 2: Bounds for Men

Gender Inequality



Figure 3: Share of Gender Inequality Caused by Parenthood (Effect on Gender Gap relative to Gap Under Parenthood)

Extensions

- ► Comparing methods Naive comp. Reasons for difference Less naive comp.
- ► Bias in event study Formal procedure ES bias estimates
- ► Bias in IV Formal procedure IV bias estimates
- ► Mental health side effects Discussion Bounds for non-depresses
- ► Relation to methodological literature Theoretical comparison Results
- ► Confidence inveral comparison Confidence intervals
- ► Inequality correcting for age De-aging partners
- ► Stable complier group Childless final period
- Estimator without DML Estimates
- Monotonicity Discussion Direction Partnered only Partnership and depression Test
- ► Testing Bensnes et al. (2023); Gallen et al. (2023) Estimates
- ► Heterogeneity Willingness to try
- Population imputation ES pop. Mother. imp. Childless imp. Effect imp.

Conclusion

New method for evaluating treatment effects under dynamic non-compliance:

Applicable to various settings involving sequential quasi-experiments

Application to estimate the career cost of parenthood in the Netherlands:

Motherhood causes up to half of gender inequality in hours and income

Accounting for selection and dynamics reconciles conflicting findings in the literature:

Substantial bias in estimates based on existing methods

External relevance:

- ▶ IUI is common; sample matches population on observables
- Alternative methods give similar results in both samples

Policy:

Large share of gender inequality may not be due to parenthood per se

Why IV and ES Estimates May Differ Within the Same Sample

- 1. Difference in weights
 - ► IV: local average treatment effect
 - ► ES: closer to the average treatment effect on the treated
- Different treated outcomes
 - ► IV: motherhood at first attempt
 - ES: motherhood at any point
- 3. Difference in control outcomes
 - ► IV: trying and failing (mental health and relationship side effects)
 - ES: potentially not trying yet
- 4. Bias due to dynamic effects or selective timing
 - IV: biased under dynamic effects
 - ES: biased under selective timing

I demonstrate that:

- 1. No explanatory power
- 2. Very limited explanatory power
- 4. Sufficient to explain the difference



Instrumental Variable vs Event Study: Percent Reduction in Earnings



Source: (Lundborg et al., 2024)

▶ "Naive" comparison with differing sub-populations and treatment definitions





Theoretical Bias

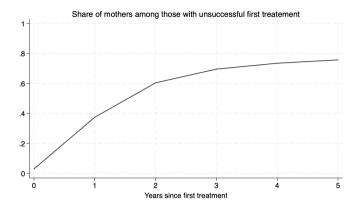


Figure 4: Motherhood among unsuccessfully treated $\tau_{RF} = 0.25 \tau_{Parenthood} - 0.75 \tau_{Delay}$ $\tau_{IV} = \tau_{Parenthood} - 3 \tau_{Delay}$

Back (for illustration restricting heterogeneity between individuals)

Bounding τ_{ATR}

Construct the moment:

$$m^{L}(G, \eta^{0}) = Y1_{\{Y < q(r(X_{1}), X_{1})\}} \frac{Z_{1}}{e_{1}(X_{1})} - Y(1 - D) \prod_{i=1}^{A} \frac{(1 - Z_{i})}{(1 - e_{i}(X_{i}))}$$

- ► G is the observed data vector
- $\triangleright \eta^0$ contains the following:

 - $q(r(X_1), X_1)$ is the $r(X_1)$ -th quantile of Y given X_1 and $Z_1 = 1$ $r(X_1)$ identifies the covariate-conditional relier share

Assumption (Conditional Sequential Unconfoundedness)

 $(Y(k), R, W) \perp \!\!\! \perp Z_j \mid X_j \text{ for all } j, k, \text{ and } X_j, A \geq j.$

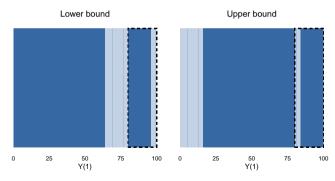
Theorem (Lower Bound)

Under conditional sequential unconfoundedness and regularity, the sharp lower bound on τ_{ATR} is $\mathbb{E}[m^L(G,\eta^0)]/\mathbb{E}[r(X_1)]$.

Intuition: Motherhood Outcome $Y_1(1)$ —Covariates

Pre-ACP covariates can help narrow the bounds:

- ► Can identify relier share at each covariate value
- Baseline bounds assume extreme scenarios where reliers have highest or lowest treated outcomes
- ► These distributions of treated outcomes might be inconsistent with conditional relier shares



Estimating the Bounds

Distribution of $m^L(G, \eta^0)$ is complicated by $q(r(X_1), X_1)$

- ► Semenova (2023) addresses a closely related inference challenge
- Double/debiased machine learning approach
- 1. Adjust $m^L(G,\eta^0)$ to make it insensitive to small error in $q(r(X_1),X_1)$
- Asymptotic inference as if $q(r(X_1), X_1)$ was known

New moment:

$$\psi^L(G,\xi^0) = m^L(G,\eta^0) + corr(G,\xi^0)$$

Identifies same parameter:

2. Sample splitting

$$\mathbb{E}[\psi^L(G,\xi^0)] = \mathbb{E}[m^L(G,\eta^0)]$$

Insensitive to estimation error in $q(r(X_1), X_1)$:

$$\partial_{\sigma(\cdot)} \mathbb{E}[\psi^{L+}(G,\xi_r)|X_1]|_{\xi_r=\xi^0} = 0$$
 a.s.

Assisted Conception Procedures

- ▶ IUI (main procedure): sperm injected into uterus
 - ▶ Minimally invasive, primary ACP in most countries
 - "Free" in NL
- ▶ IVF (secondary procedure): embryo inserted into uterus
 - Invasive treatment, performed under sedation/anesthesia
 - Eggs retrieved through the vaginal wall using a specialized needle
 - ▶ In NL, first 3 free; each subsequent costs between 1000 and 4000 EUR



Institutions

- Dutch family friendly polices similar to OECD average
 - ▶ 16 weeks of fully paid pregnancy+maternity leave
 - ▶ 1 week of paternity leave
 - Average time in child care similar to OECD average
 - ▶ Net child care cost 10% median household income
- Dutch employment intensity similar to OECD average
 - Employment among parents and non-parents relatively high
 - Part time work much more common
 - ▶ Approximately 15% two-parent families have both partners working part-time

Back

Data

Administrative data from Statistics Netherlands

- Comprehensive hospital records cover fertility treatments from 2012 to 2017: procedure date and type
 - Success imputed as having child born within 10 months
- ► Tax records cover work hours and income from 2011 to 2023
 - Include maternity leave and pay
 - Main bounds account for uncertainty around actual work hours
- Birth dates, legal family connections, cohabitation
- Dispensed medication registry

Main sample: cohabiting opposite-sex couples undergoing IUI for their first child between 2013 and 2016: 15,523

Back

ToC

Overview of Descriptives

- ► First and subsequent ACP success uncorrelated with past labor market outcomes condiditional on age Table first Table later
 - ▶ Support for independence of Z_j and $(Y_1(1), Y_0(0))$
- Success probability stable across ACPs conditional on age Figure
 - ▶ Support for independence of Z_j and W
- Representative sample worked less and had lower income before parenthood, but differences relatively small Table
 - ACP sample older before parenthood

Back (summary)

Balance in 1st ACP

Table 1: First IUI Outcomes and Descriptives

	Success (1)	Fail (2)	Dif. (1)-(2)	IPW dif. (1)-(2) cond.	Rep. (5)	Suc. vs rep (1)-(5)
Work (W)	0.912 [0.283]	0.916 [0.277]	-0.004 (0.008)	-0.009 (0.008)	0.936 [0.244]	-0.024 (0.007)
Work (P)	0.894	0.885	(0.009)	(0.002)	0.897	-0.002 (0.008)
Hours (W)	1300.012 [547.832]	1298.876 [558.316]	1.136 (15.730)	-1.951 (16.119)	1310.923 [544.468]	-10.911 (14.554)
Hours (P)	1513.337 [635.121]	1494.541 [656.050]	18.796 (18.457)	3.345 (19.041)	1497.603 [651.043]	15.734 (17.403)
Earn. 1000s EUR (W)	29.358 [18.000]	29.648 [18.911]	-0.290 (0.531)	0.203 (0.561)	26.555 [15.989]	2.803 (0.427)
Earn. 1000s EUR (P)	38.082 [25.425]	38.060 [26.525]	0.022 (0.745)	0.322 (0.774)	33.862 [24.148]	4.220 (0.646)
Bachelor deg. (W)	0.512	0.494	0.018		0.518	-0.007 (0.013)
Bachelor deg. (P)	0.425 [0.494]	0.410 [0.492]	0.014 (0.014)		0.430 [0.495]	-0.005 (0.013)
Age (W)	31.373	32.060 [4.265]	-0.687 (0.119)		28.840 [3.896]	2.533 (0.104)
Age (P)	34.088 [4.968]	34.856 [5.500]	-0.768 (0.154)		31.415 [4.803]	2.673 (0.128)
Observations	1,411	11,323			171,180	
Joint p-val.			0.001	0.955		0.000

Note: Success – average among women whose first IUI succeeded; Fail – average among women whose first IUI failed; Dif. – difference between Success and Fail; IPW dif. – difference adjusted for age and education using inverse probability weights from the baseline specification; Rep. – average in representative sample of women who conceived their first child without assisted conception procedures; Suc. vs rep – difference between Success and Rep. Reference year: year of first IUI (IUI sample); 9 months before first birth (representative sample). IUI sample: women who undervent intrauterine insemination for their first child between 2013 and 2016, with no prior assisted conception procedures, cohabiting with a male partner in the year prior to the reference year. Representative sample: women with no assisted conception procedures before first birth, cohabiting with a male partner in the year prior to the reference year, where Pail Pai

Balance in Subsequent ACPs

Table 2: Balance in Later ACPs

	Z_2	Z_3	Z_4	Z_5	Z_6	Z 7	Z_8	Z_9	Z_{10}
Work (W)	0.009	-0.004	0.022	0.014	0.039	-0.003	-0.011	0.022	0.030
	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.017)	(0.018)	(0.019)	(0.024)
Work (P)	0.006	0.016	0.012	0.020	-0.004	-0.004	-0.019	0.017	0.030
	(0.010)	(0.010)	(0.012)	(0.012)	(0.015)	(0.015)	(0.019)	(0.020)	(0.027)
Hours (W)	32.885	-4.482	52.999	41.332	81.957	11.894	-18.836	72.659	24.819
	(18.721)	(20.032)	(21.045)	(22.686)	(25.131)	(31.187)	(32.937)	(38.210)	(48.490
Hours (P)	21.655	24.730	23.756	38.965	9.666	-6.580	-28.458	30.525	43.722
	(21.018)	(21.089)	(23.574)	(25.255)	(30.585)	(31.513)	(37.976)	(44.856)	(52.821
Income 1000s € (W)	1.481	-0.015	1.685	1.802	2.086	0.150	-0.043	0.866	-0.444
	(0.615)	(0.624)	(0.767)	(0.830)	(0.913)	(1.000)	(1.092)	(1.234)	(1.629)
Income 1000s € (P)	-0.749	1.002	2.040	0.800	0.774	0.025	0.259	-0.324	0.149
	(0.835)	(0.912)	(1.066)	(1.115)	(1.424)	(1.424)	(1.563)	(1.737)	(2.203)
Observations	12,974	10,774	8,726	6,977	5,411	3,944	2,723	1,850	1,174
Joint <i>p</i> -val.	0.175	0.976	0.234	0.303	0.140	1.000	0.956	0.704	0.917

Note: Each column describes the difference in average characteristics between women for whom the respective ACP succeeds and those for whom it fails, among those who undergo the procedure, using inverse probability weights for each ACP following the main specification. Labor market outcomes and age measured year before first treatment. (W) - woman, (P) - partner. Standard errors in parentheses.

ACP histories Back (summary) Back (detailed descriptives)

Estimated Success Probabilities

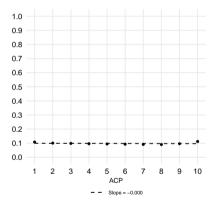


Figure 5: Estimated Success Probabilities

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Comparison to Representative Sample

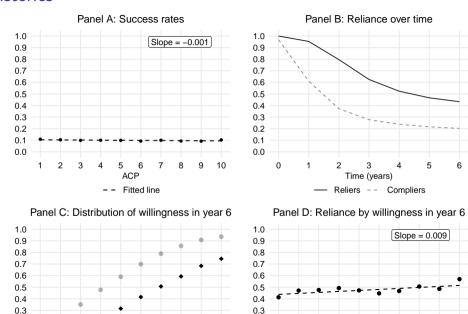
Table 3: Full Sample, Reliers, and Representative Sample

	Success (1)	Fail (2)	Reliers (3)	Rep. (4)	Success vs rep. (1)-(4)	Rel. vs rep (3)-(4)
Work (W)	0.882	0.863	0.820	0.801	0.080	0.019
	[0.323]	[0.344]	[0.333]	[0.399]	(0.010)	(0.005)
Work (P)	0.884	0.865	0.849	0.783	0.101	0.066
	[0.320]	[0.342]	[0.344]	[0.412]	(0.010)	(0.005)
Hours (W)	1240.315	1207.860	1117.711	1076.204	164.111	41.508
	[604.666]	[635.194]	[582.334]	[696.245]	(16.856)	(8.412)
Hours (P)	1474.530	1438.590	1390.699	1250.948	223.582	139.752
	[658.231]	[695.692]	[662.920]	[793.536]	(19.211)	(9.576)
Income 1000s € (W)	28.065	27.418	24.976	21.362	6.703	3.615
	[19.559]	[20.219]	[15.359]	[18.330]	(0.444)	(0.222)
Income 1000s € (P)	37.205	36.952	35.299	28.107	9.098	7.193
	[26.482]	[29.452]	[24.304]	[29.076]	(0.704)	(0.351)
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	28.713	2.926	4.767
	[4.015]	[4.383]	[3.897]	[4.658]	(0.113)	(0.056)
Age (P)	34.675	35.461	36.580	28.713	5.962	7.868
	[5.513]	[5.996]	[3.928]	[4.665]	(0.113)	(0.057)
Observations	1,714	13,809	4,882	376,152		

Note: Labor market outcomes measured year before first ACP for main smple and year and 9 months before birth of first child for the representative sample is expected to match the main sample by any of conception. Average relier outcomes are based on sample representative sample is expected to match the main sample by any of conception. Average relier outcomes are based on sample representative sample is expected to match the main sample by any of conception. When the sample representative sample is expected to match the sample representative sample is expected to make the sample representative sample sample sample representative sample representative sample sample representative sample sample sample representative sample sample

ACP Histories

ToC.



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

Relation to Methodological Literature



Comparison with Lee (2009)

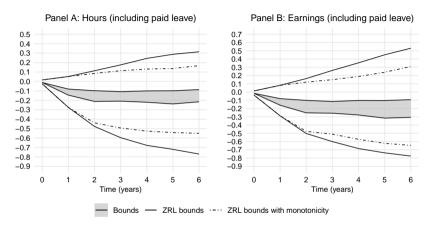


Figure 7: Comparison with Lee (2009) Bounds for Effects on Women

Less Naive Comparison to Existing Methods

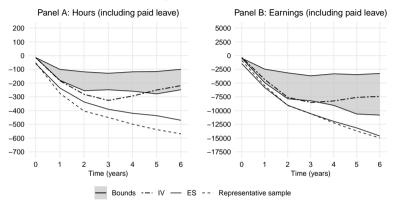


Figure 8: Estimates Using on Different Methods (Absolute Effects)

- ▶ Using women whose ACP succeeds for ES makes treatment definition consistent
- ▶ The three methods still target different sub-populations



Quantifying Bias in Event Study

Kleven et al. (2024) compare mothers t years after childbirth to women one year before

- Most gender inequality is explained by these differences between women
- Event study estimates may be biased due to selective timing
- ▶ But differences from IV/bounds need not imply bias, even in the same sample
- 1. I proxy fertility timing using the timing of first ACP
- Compare the actual trajectories of women who attempted conception but remained childless with those imputed from women who are about to attempt conception but ultimately remain childless
- Event study comparison of women with different timing absent children
- ► Same population as bounds: selection vs causal effects directly comparable



Placebo Event Study

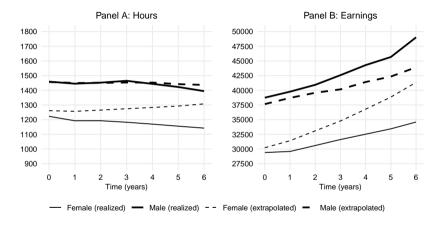


Figure 9: Placebo Event Study (Absolute)



Gender Inequality: Causal vs Selection

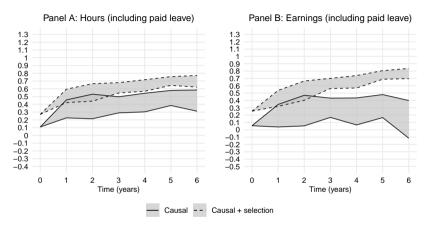


Figure 10: Share of Gender Inequality Explained by Selection and Parenthood

Quantifying Bias in IV

Instrumental Variable (Lundborg et al., 2017):

- ▶ I have bounded τ_{ATR} allowing for dynamic effects
- \blacktriangleright I can point-identify au_{ATR} assuming static effects à la instrumental variable
- ▶ Subtracting it from bounds on τ_{ATR} gives bounds on bias



Mental Health and ACPs

Mental health consequences associated with failure to conceive are a part of the story:

 Unmet fertility goals may negatively impact mental health, and in turn, labor market outcomes

There are, however, additional concerns:

- ▶ Mental health issues caused specifically by failed conception or ACPs (external)
 - ► Focusing on artificial insemination helps mitigate this
- Large impacts unique to ACP families (external)
- Worsened mental health by threatening monotonicity (internal)

In practice, these impacts are likely small (Lundborg et al., 2024)

Antidepressant uptake Back (extensions) Conclusion

Monotone Bounds for Non-depressed Childless Women

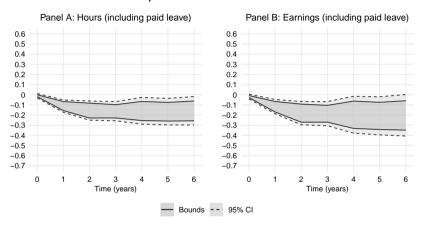
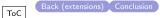


Figure 11: Monotone Bounds for Women Who Would Not Uptake Antidepressants if They Were to Remain Childless



Confidence Intervals

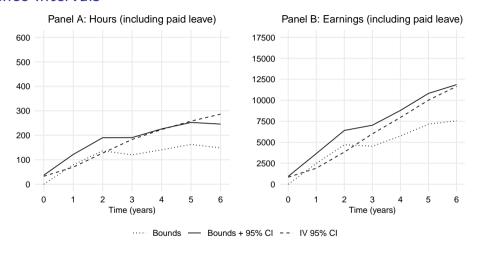


Figure 12: 95% CI for Different Methods (Absolute)

Monotonicity

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 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



Monotone Bounds: Women who Remain Childless

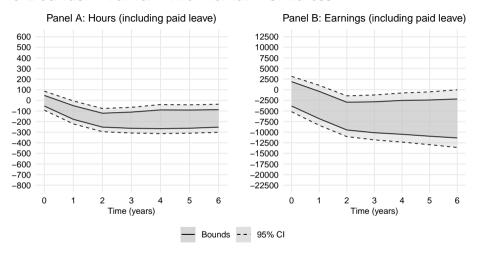
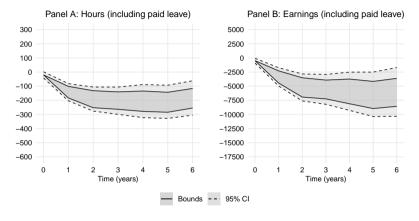


Figure 13: Monotone Bounds Using Completed Fertility (Absolute)

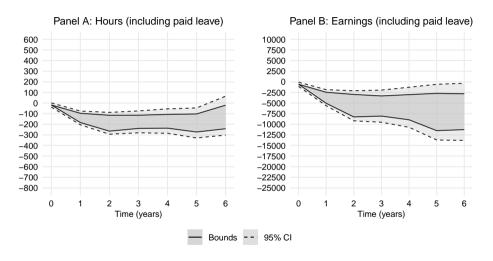
Back

Simple estimator



- $\mathbb{E}[Y_1(1)|R=1] = \mathbb{E}[g(X_1) + \varepsilon|R=1]$
- $ightharpoonup \mathbb{E}[g(X_1)|R=1]$ identified on chillness reliers using baseline method
- ▶ Only need to bound $\mathbb{E}[\varepsilon|R=1]$

Relaxing Monotonicity Direction





Relaxing Monotonicity to Partnered Women

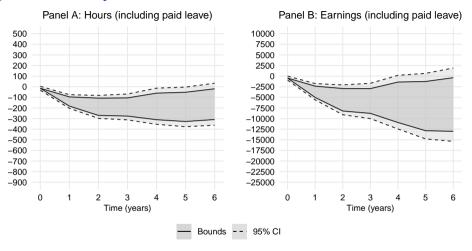


Figure 14: Monotone Bounds Using Women Who Stay Partnered



Relaxing Monotonicity for Depression and Partnership

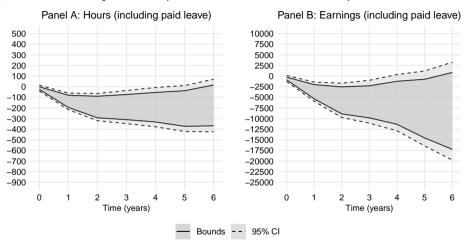
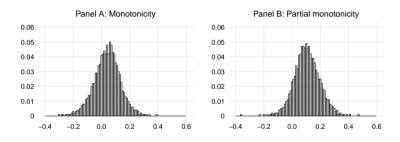


Figure 15: Monotone Bounds For Women Who Stay Partnered and Do Not Uptake Antidepress.

Testing Monotonicity





Heterogeneity by Willingness to Undergo Procedures

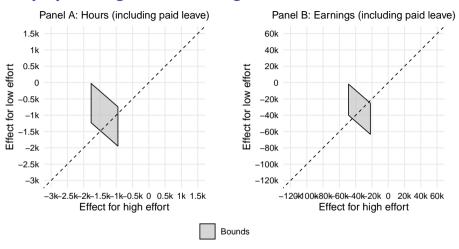


Figure 16: Cumulative Outcomes 6 Years After, G Above or Below 6

Monotone Bounds: Excluding Depression

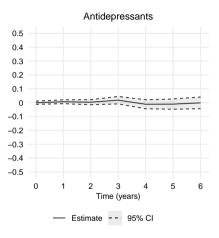


Figure 17: Effect on Antidepressant Take-Up

Monotone Bounds: Correcting for Partner's age

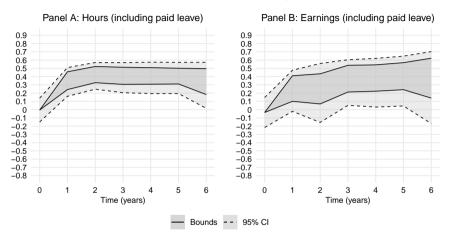


Figure 18: Monotone Bounds Using Male Income at Same Age as Female

Testing the Plug-in Approach

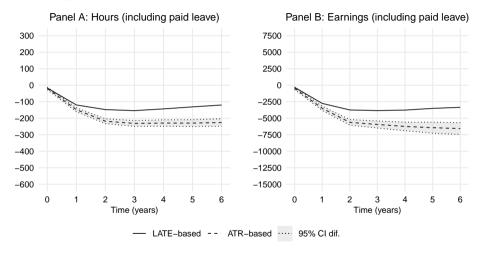


Figure 19: Plug-In Estimators Exploiting Different Numbers of Treatments

Event Study: Population vs IUI Sample



Figure 20: ES for Population and Women with First IUI Success

Imputing Population Motherhood Outcomes Using IUI Sample



Figure 21: Population Outcomes vs IUI-Imputation (Age & Education)

Back

Imputing Population Childless Outcomes Using IUI Sample



Figure 22: Population Outcomes vs IUI-Imputation (Age & Education)

Back

Event Study vs IUI-imputation for Population



Figure 23: Event Study vs IUI-Imputation for Population (Age & Education)

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