Child Penalty Estimation and Mothers' Age at First Birth

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Motivation (I)

- Gender inequality remains prevalent in the labor markets around the world
- Major reason: career costs of motherhood (Goldin, Kerr, and Olivetti 2022; Blundell et al. 2021; Adda, Dustmann, and Stevens 2017)
- Correctly tracking the costs and studying the mechanisms is vital to understand gender inequality and to give informed policy advice
- Estimating **child penalties** (as event studies around childbirth: Kleven, Landais, and Søgaard 2019) has recently become one of the most popular methods in the field

Motivation (II)

A common child penalty estimation pools together mothers who give birth at different ages.

HOWEVER (1) **Mothers are different** depending on their age at first birth

- Selection into different career paths/occupations is based on desired fertility and associated with its timing (Adda, Dustmann, and Stevens 2017)
- Earnings and wages positively correlated with age at birth (Wilde, Batchelder, and Ellwood 2010; Goldin, Kerr, and Olivetti 2022)

HOWEVER (2) **Effects of motherhood change** over time after birth

$\Longrightarrow$ Potential threat of differential losses by age at birth and over time, or **heterogeneous treatment effects**

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This Paper

- Shows that the conventional approach yields substantially biased estimates
- Proposes a new approach that ensures clean and valid cohort-specific control groups: stacked DiD estimation with a rolling window of control cohorts over age at 1st birth
- Application: effects of motherhood on labor market outcomes by age at 1st birth

Contributions:

- Career effects of motherhood:

  Kleven, Landais, and Søgaard (2019), Kleven, Landais, Posch, et al. (2019), Andresen and Nix (2022), Kuziemko et al. (2018), Bütikhofer, Jensen, and Salvanes (2018), Angelov, Johansson, and Lindahl (2016), and Fitzenberger, Sommerfeld, and Steffes (2013).
- Issues with DiD and TWFE models if treatment effects are heterogeneous:

  Goodman-Bacon (2021), de Chaisemartin and D'Haultfoeuille (2020), Sun and Abraham (2021), and Callaway and Sant'Anna (2021); overviews: Roth et al. (2022) and de Chaisemartin and D'Haultfoeuille (2022).

Data

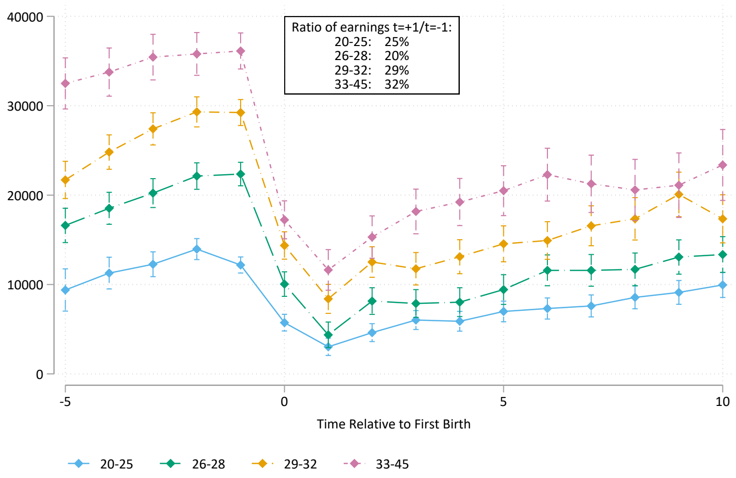
- Sample of Integrated Labor Market Biographies (SIAB)
  - German administrative social security records
  - 1975-2019

  $\longrightarrow$ Used to illustrate the problems and to apply the new approach (cohort-specific analysis)

- German Socio-Economic Panel (SOEP)
  - Survey on labor market outcomes and multiple socio-economic characteristics
  - 1984-2020

  $\longrightarrow$ Used to show the heterogeneity in outcomes of mothers by age at birth

Heterogeneity by Age at First Birth: Earnings



Annual Earnings of Women by Age at First Birth (SOEP).

More Dimensions of Heterogeneity

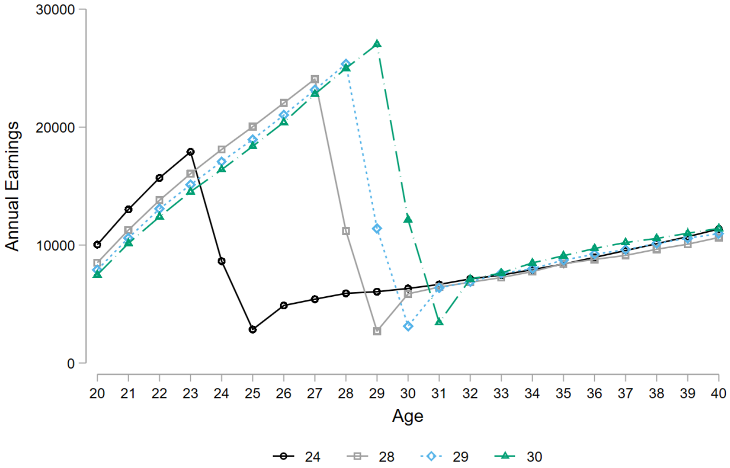
Child Penalty Estimation under Heterogeneity (I)

- Stylized example:
  - SIAB data
  - 4 cohorts of mothers (give birth at 24, 28, **29**, 30)
  - 2 periods (ages 28 and 29)
  - Aim: estimate treatment effect of birth at age 29
- Goodman-Bacon (2021) decomposition of the static DiD estimate:

$$Y_{it} = \beta \times \text{treated}_{it} + \gamma_i + \lambda_t + \varepsilon_{it}$$

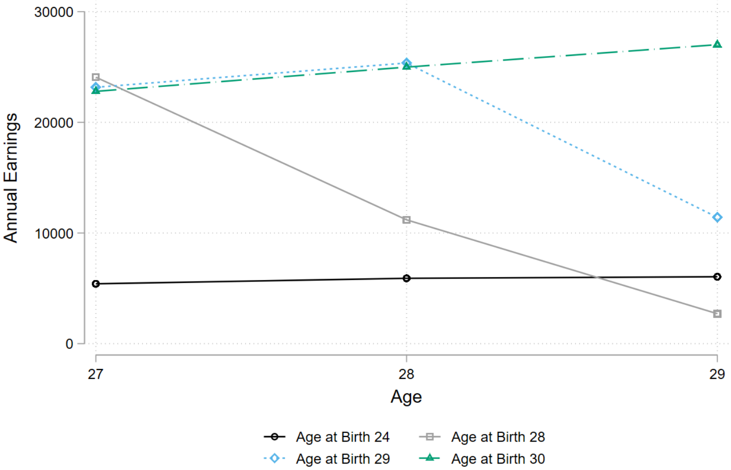
Where Y_{it} are annual earnings for mother i at age t, γ_i are individual FEs and λ_t are age FEs, treated_{it} is a treatment status indicator, which takes the value 0 if the individual is not treated yet and switches to 1 when the treatment happens and stays 1 thereafter.

Child Penalty Estimation under Heterogeneity (II)



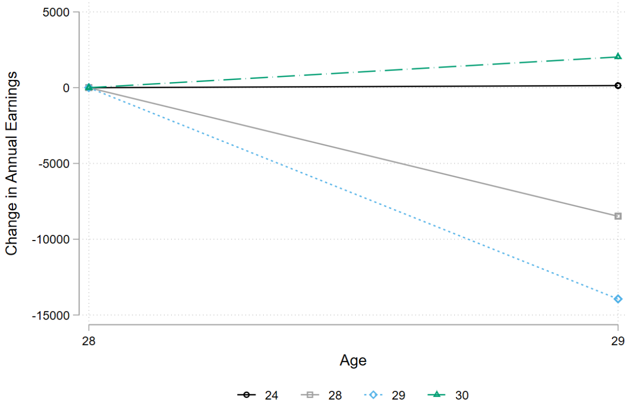
Average earnings of mothers around birth for four age levels at 1st birth (24, 28, 29, 30)

Child Penalty Estimation under Heterogeneity (III)



Average earnings in levels for age range 27 to 29.

Child Penalty Estimation under Heterogeneity (IV)



Changes in average earnings for age range 28 to 29.

- DiD average:
  Euro −11.6 K
- **Clean comparison** (to age 30):
  Euro −16 K, weight: 33.8%
- **Forbidden comparisons** (to ages 24 and 28):
  Euro −9.3 K, weight: 66.2%

$\Longrightarrow$ Bias:
Euro 4.4 K (> ⅓ of average estimate)

Full decomposition

Contamination

Child Penalty Estimation under Heterogeneity (V)

- Large heterogeneity in characteristics of women by age at childbirth (age at birth strongly correlates with labor market outcomes)
- Therefore issues with the validity of the commonly used control groups:
  - all not-yet-treated (Callaway and Sant'Anna 2021): all older first-time mothers including the oldest
  - never-treated (Sun and Abraham 2021): childless women (or men?)
  - last-treated (Sun and Abraham 2021): the oldest first-time mothers

$\Longrightarrow$ New estimators not readily applicable

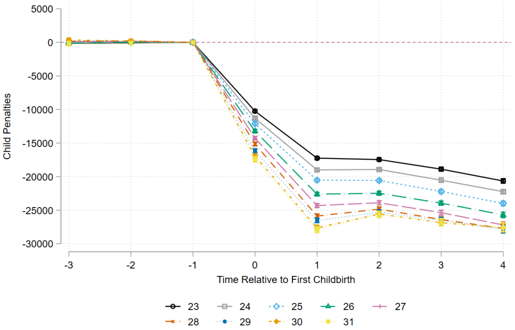
Re-scaling

New Approach: Intuition

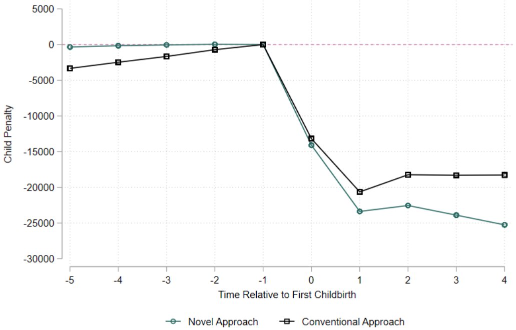
- Combine stacked DiD and a rolling window of control cohorts over age at birth (building on ideas from Cengiz et al. 2019; Callaway and Sant'Anna 2021)
- Create a clean and valid control group specific to each cohort
  - Only use pre-birth observations
    $\longrightarrow$ no "forbidden" comparisons
  - Only close observations in terms of age at first birth
    $\longrightarrow$ Ensures comparability of treated and control group (test: cohort-specific pre-trends)
- Estimate both cohort-specific and (weighted-)average effects
- Application with 5 next cohorts included in each control group (estimate effects up to year +4)

Detailed Model

Application: Cohort-Specific and Average Child Penalties



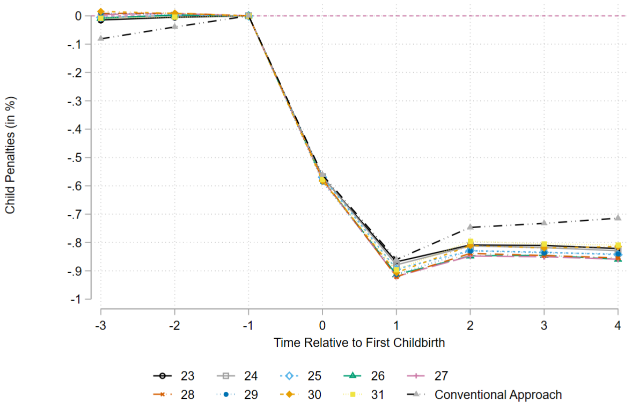
Post-birth earnings losses by age at first childbirth.



Average post-birth earnings loss.

Earnings losses after the first childbirth.

Application: Child Penalties in Percentage Terms



- Average child penalty of ≈ -85 percent
- 15 percentage points (20 percent) larger than conventional estimate

Earnings losses after the first childbirth in relative terms (scaled by counterfactual outcomes calculated from the control groups' outcomes).

Re-scaling Methods

Cumulative Earnings

Occupational Rank

Concluding Remarks

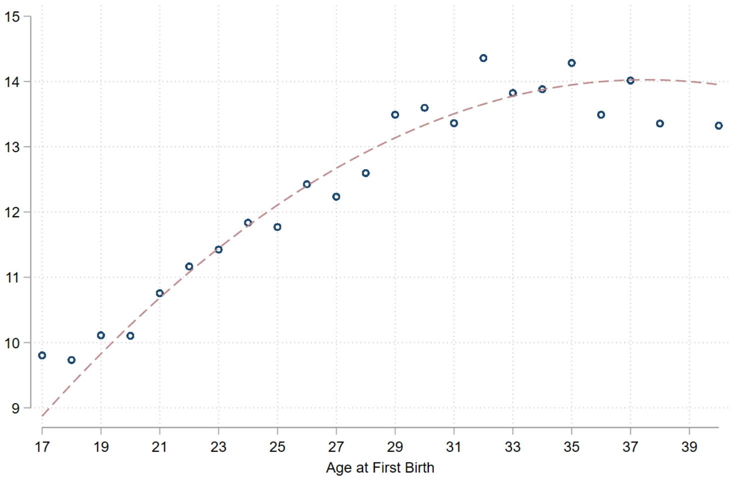
- Mothers and child penalties are heterogeneous by age at first birth and over time after birth
  - $\Longrightarrow$ *Forbidden comparisons* and *contamination* lead to biased estimates
  - $\Longrightarrow$ Control groups of existing alternative DiD estimators not valid

- We suggest a new estimation approach based on a stacked DiD with cohort-specif control groups of comparable not-yet-treated mothers
- Application to German admin data
  - Shows that previous studies substantially underestimate the earnings penalty of motherhood
  - Confirms high heterogeneity in child penalties (suggests differential effects of policies, eg. childcare supply)

Read the discussion paper:

Appendix

Heterogeneity by Age at First Birth: Educational Attainment



Total Years of Education of Women by Age at First Birth (SOEP).

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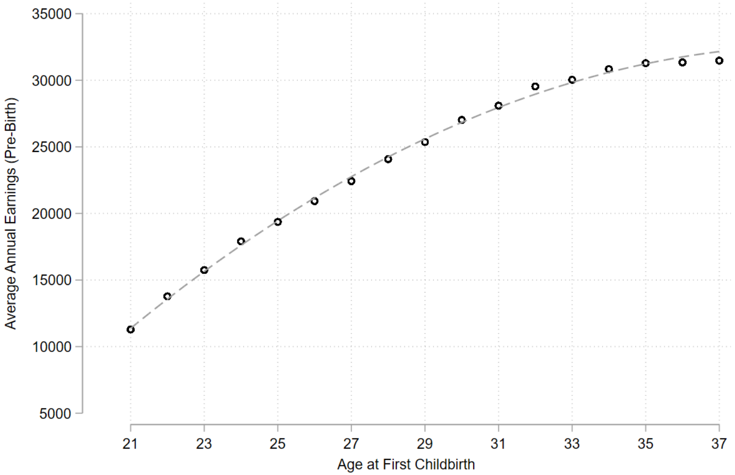
Heterogeneity by Age at First Birth: Pre-birth Earnings



Annual labor earnings in the pre-birth year by age at first birth (SIAB).

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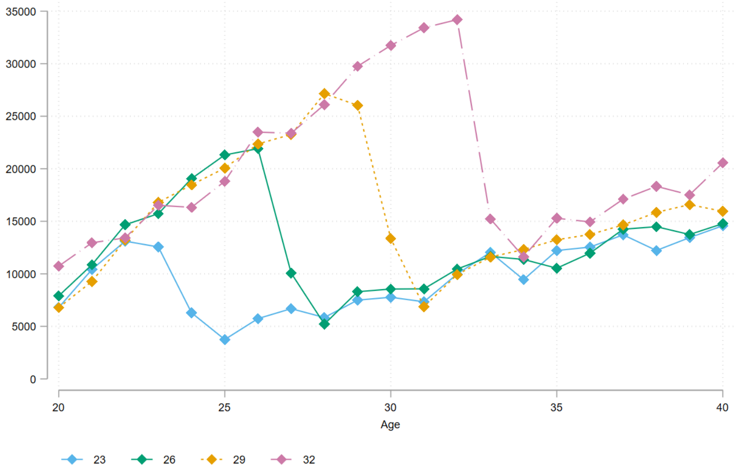
Heterogeneity by Age at First Birth: Earnings around Birth



Average earnings of mothers around birth for four levels of age at first birth, incl. zeros (SOEP).

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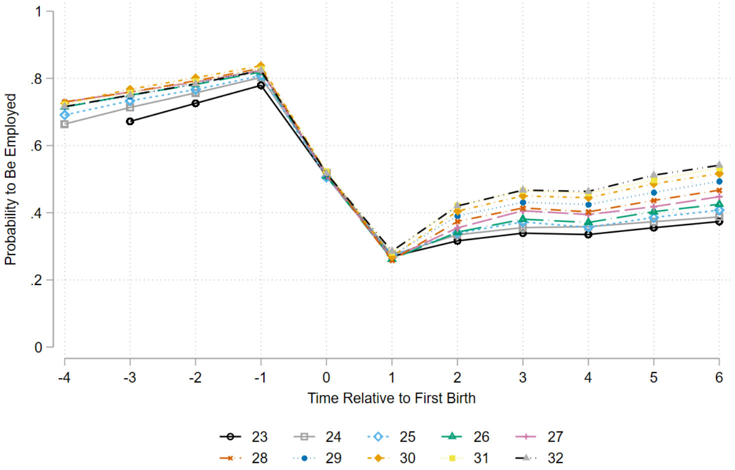
Heterogeneity by Age at First Birth: Employment



Employment rates around the first childbirth by cohort (SIAB).

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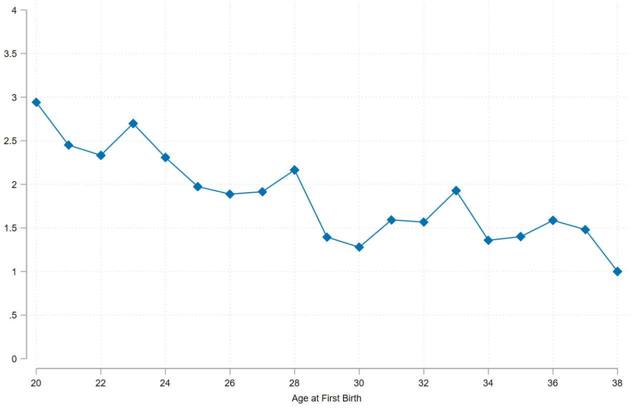
Heterogeneity by Age at First Birth: Average Length of Employment Break



Average length of employment break by age at childbirth (conditional on returning to work) (SOEP).

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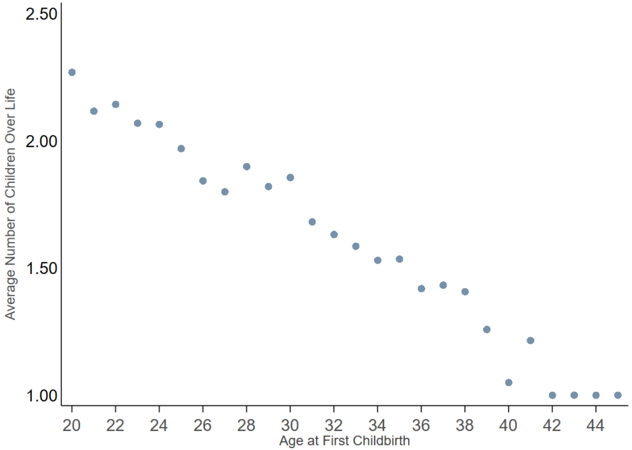
Heterogeneity by Age at First Birth: Average Number of Children



Average total number of children by age at first childbirth (SOEP).

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Stylized Example: Goodman-Bacon Decomposition

Decomposition of average estimate: "Clean" and "forbidden" comparisons

	Average	"Clean" (to 30)	All "Forbidden" (to 24 and 28)	"Forbidden" (to 24)	"Forbidden" (to 28)
Treatment status	−11,562***	−15,976***	−9,307***	−14,158***	−5,430***
	(142)	(173)	(160)	(173)	(202)
Age FE (Age=29)	-2,384	2,030	-4,639	212	-8,516
Person FEs	Yes	Yes	Yes	Yes	Yes
Included cohorts	24, 28, 29, 30	29, 30	24, 28, 29	24, 29	28, 29
Estimation window	28–29	28–29	28–29	28–29	28–29
Weight in average		33.8%	66.2%		
Weight in "forbidden"				44.4%	55,6%

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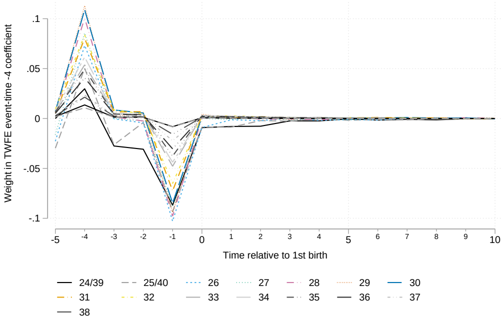
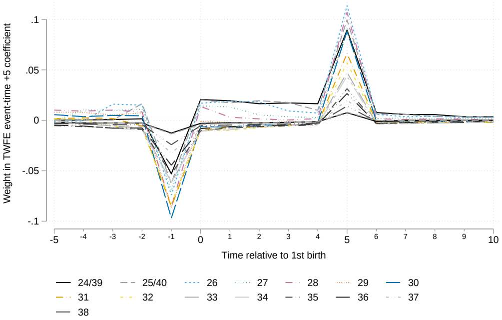
Decomposition of Weights (Sun and Abraham 2021)



4 years before childbirth.



5 years after childbirth.

Sun and Abraham (2021) decomposition of weights: “contamination” from other periods.

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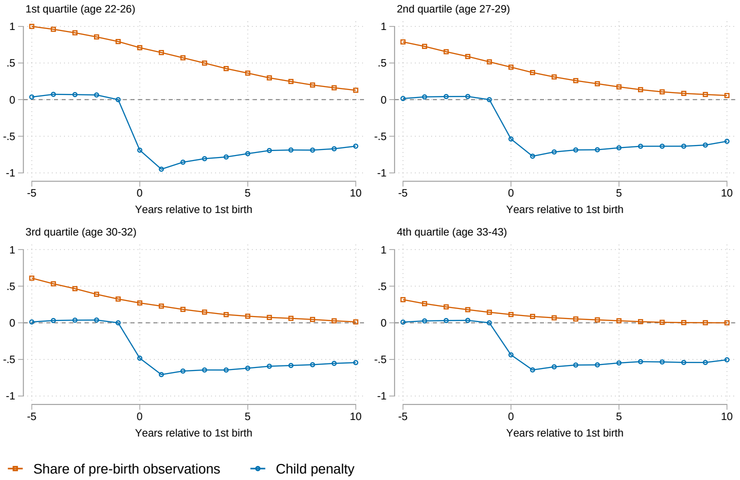
Re-scaling

Event-study estimates are often re-scaled with

$$P_l = \hat{\beta}_l / \mathrm{E}[\tilde{Y}_{it} | l],$$

ie. predicted earnings over age and year FEs.

$\Longrightarrow$ Large fraction of this "counterfactual" is made up of post-birth observations.



Composition of counterfactual earnings $\mathrm{E}\left[\tilde{Y}_{it} | t\right]$.

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New Approach: Model

- Cohort-specific penalties for each sub-event:

$$Y_{ias} = \sum_{l=-L_{min}, l \neq -1}^{L^{max}} \beta_l^s \times \mathbb{1}[a - a_i^0 = l] \times \mathbb{1}[a_i^0 = s] + \gamma_{as} + \lambda_{is} + \varepsilon_{ias}. \tag{1}$$

(i: mothers; s: cohort; a: age; $l \in [L_{min}, L^{max}]$: estimation window; control group for ages at birth $[a+1, a+N_{cc}]$)

- Average penalties across cohorts: cohort-specific estimates weighted by sample shares of each cohort (following Sun and Abraham 2021)

$$\hat{\beta}_l = \sum_{s=S_{min}}^{S_{max}} \frac{N_s}{N} \times \hat{\beta}_l^s, \tag{2}$$

(N_s: number of observations per cohort; N: total number of observations)

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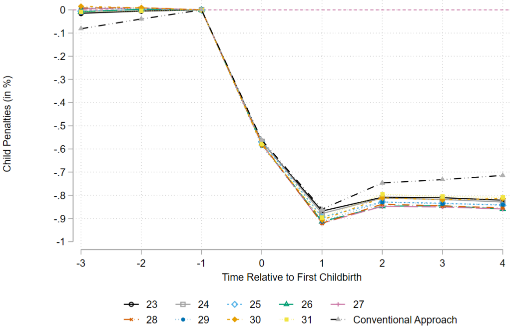
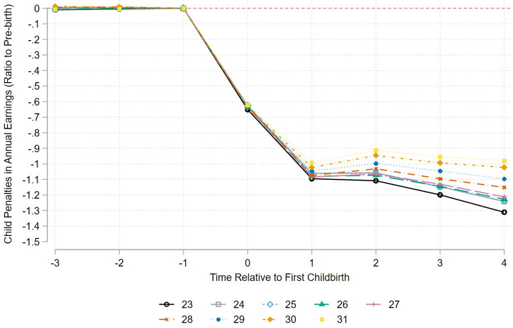
Re-scaling Methods: Comparison



Annual labor earnings losses after the first childbirth (relative to **counterfactual** levels).



Annual labor earnings losses after the first childbirth (relative to **pre-birth** levels).

Re-scaled labor earnings losses after the first childbirth.

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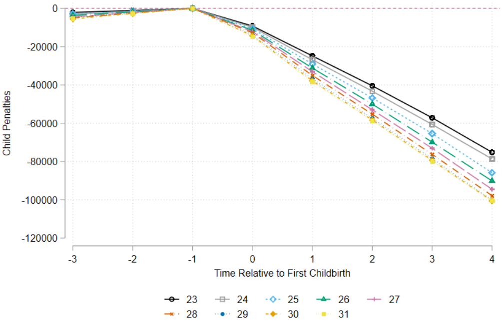
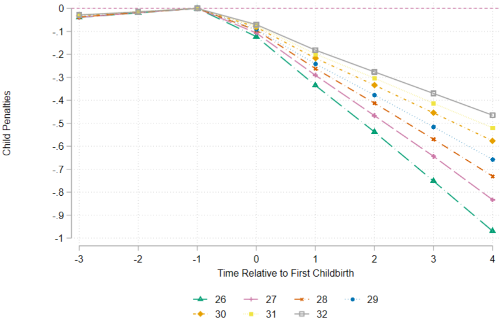
Application: Cumulative Earnings



Absolute losses in cumulative earnings.



Relative losses in cumulative earnings.

Cumulative earnings losses after the first childbirth by cohort (scaled by pre-birth levels).

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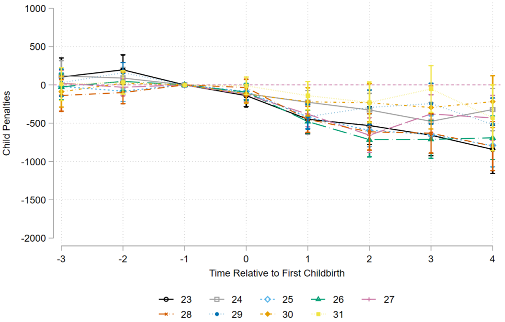
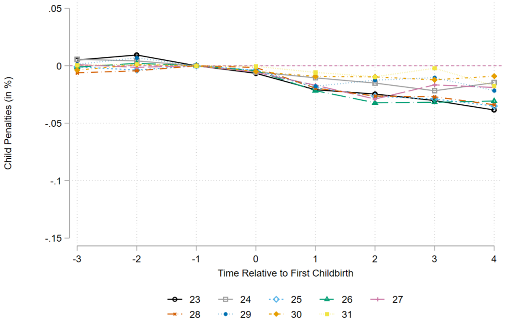
Application: Occupational Rank



Development of occupational ranks in absolute terms.



Development of occupational ranks in relative terms.

Development of occupational ranks after the first childbirth by age at first birth.

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