Difference-in-differences and event studies

with an application to the child penalty

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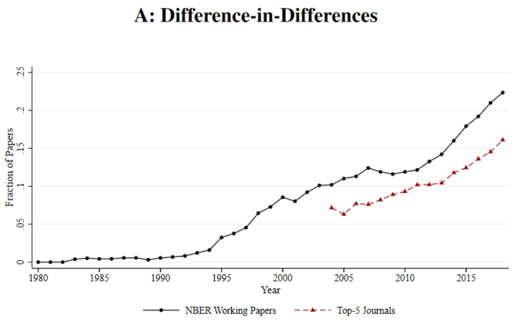
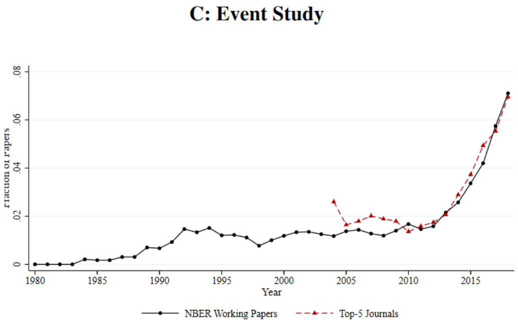
A popular method





Outline

1. Difference-in-differences and event studies
    - Canonical (2-by-2)
    - Staggered
2. Kleven, Landais, Søgaard (2019)
3. Casarico and Lattanzio (2021)
4. Applications in Stata

Difference-in-differences

"Canonical" 2-by-2 DiD – special case of a longitudinal model: compare outcomes

- before and after the treatment ($Post_t = 0$ and $Post_t = 1$, respectively)
- between the treated and the controls ($D_i = 1$ and $D_i = 0$, respectively)

The change in outcomes for the controls (which should not be affected by the treatment) provides a counterfactual for the change in outcomes for the treated in the absence of treatment

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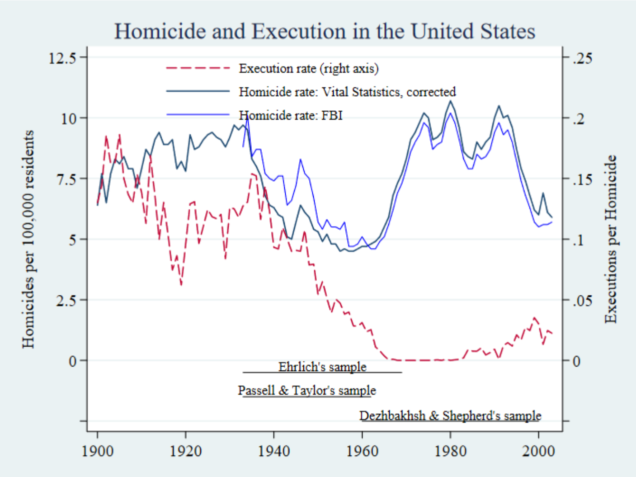
Main identifying assumption

parallel paths in the absence of treatment (<u>not</u> necessarily same level)

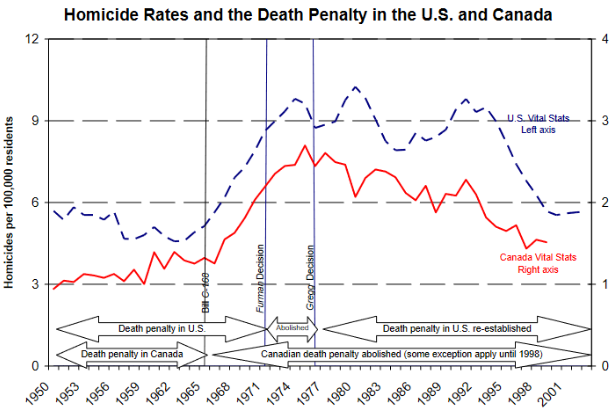
Difference-in-differences

Example



Difference-in-differences

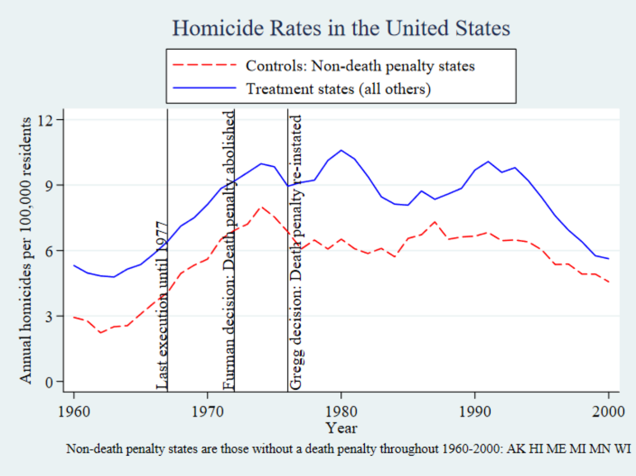
Example



- **importance of the control group**

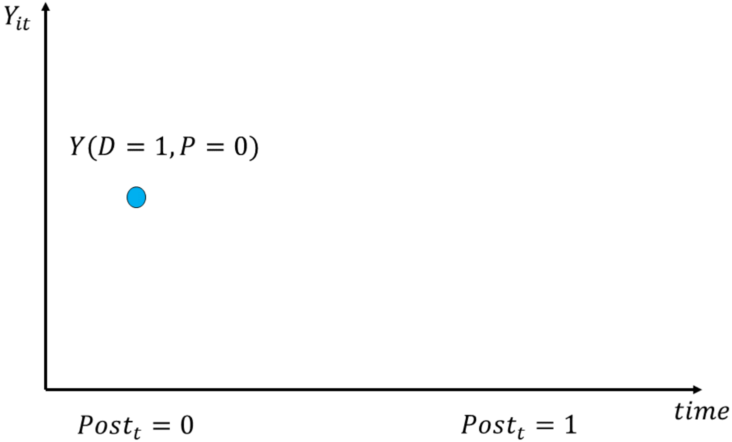
Difference-in-differences

Example

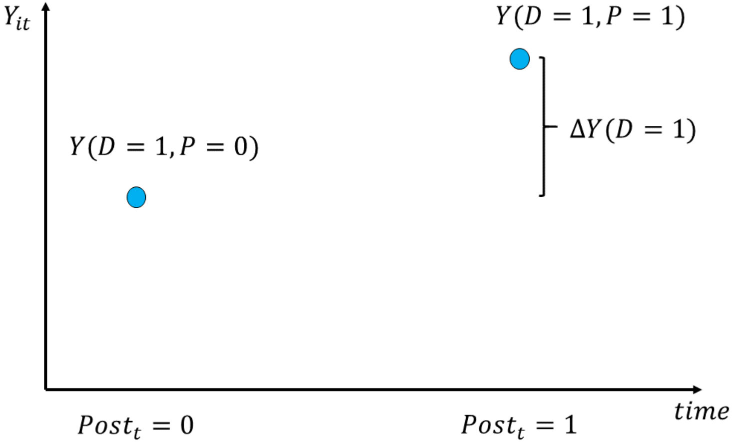


- **importance of the control group**

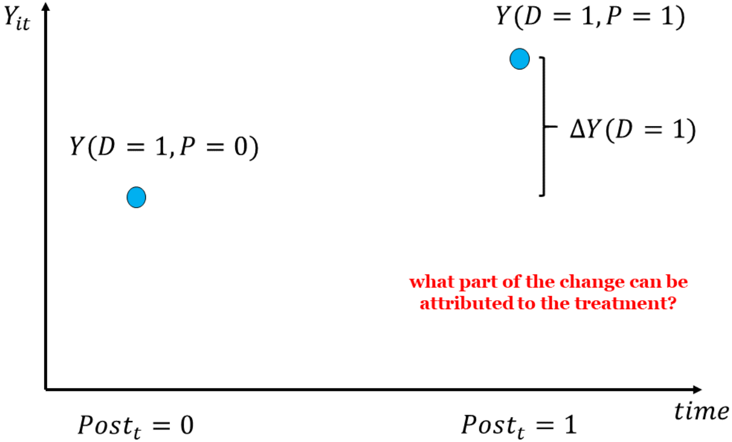
Difference-in-differences



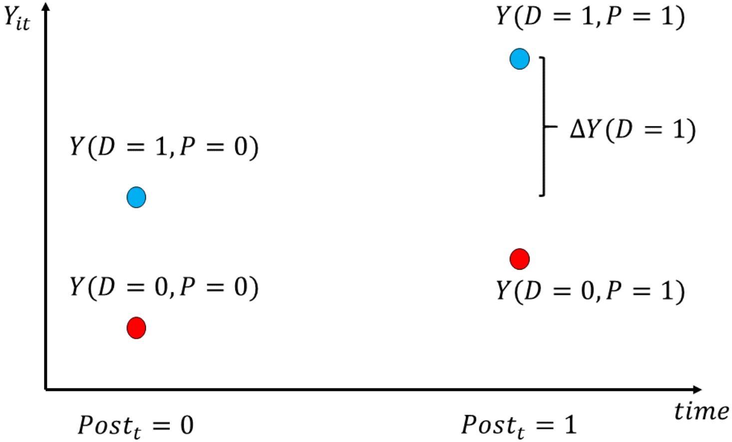
Difference-in-differences



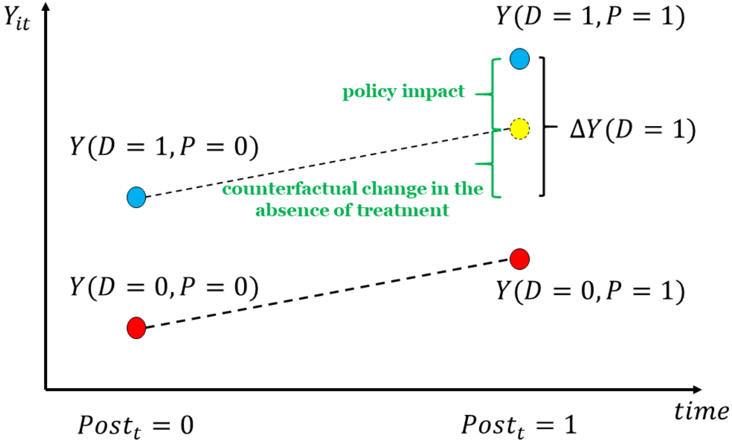
Difference-in-differences



Difference-in-differences

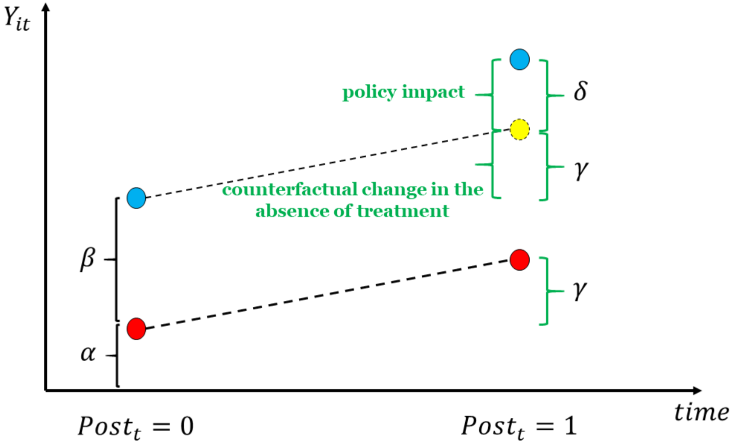


Difference-in-differences



Difference-in-differences

- In regression form: $Y_{it} = \alpha + \beta D_i + \gamma Post_t + \delta D_i \cdot Post_t + \epsilon_{it}$



Difference-in-differences

- In regression form: $Y_{it} = \alpha + \beta D_i + \gamma Post_t + \delta D_i \cdot Post_t + \epsilon_{it}$
- With more than 2 units and/or periods can control for more dimensions of heterogeneity

I. unit fixed effects (drop D_i): $Y_{it} = \alpha + \theta_i + \gamma Post_t + \delta D_i \cdot Post_t + \epsilon_{it}$

II. unit & time fixed effects (drop D_i and $Post_t$): $Y_{it} = \theta_i + \eta_t + \delta D_i \cdot Post_t + \epsilon_{it}$

III. dynamic DiD – **Event study**

$$Y_{it} = \theta_i + \eta_t + \sum_{k=-T}^{+T} \delta_k D_i \cdot 1(t = k) + \epsilon_{it}$$

Including lags into the DiD model is an easy way to analyze pre-treatment trends

Leads can be included to analyze whether the treatment effect changes over time after assignment

Staggered difference-in-differences

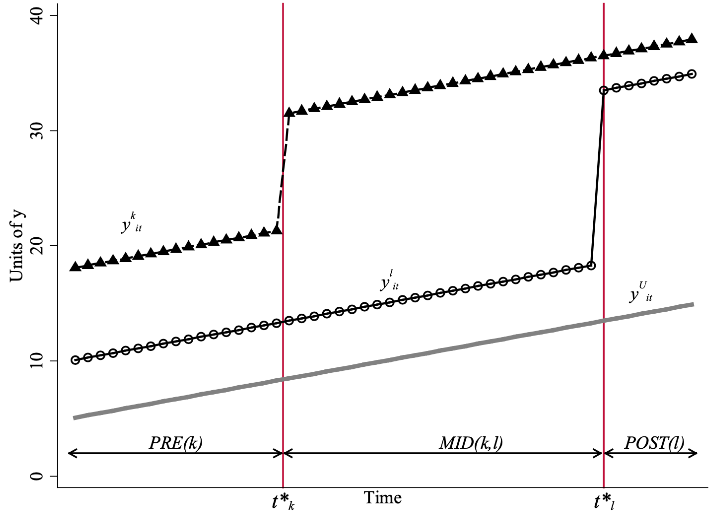
Most DiD applications diverge from the 2-by-2 setting because treatment occurs at different timings $\rightarrow$ **Staggered DiD**

$$Y_{it} = \theta_i + \eta_t + \delta D_{it} + \epsilon_{it}$$

- θ_i: unit fixed effects
- η_t: time fixed effects
- D_{it}: dummy variable for treated units (switching after t_i^*, treatment timing for each i)

Staggered difference-in-differences

Figure 1. Difference-in-Differences with Variation in Treatment Timing: Three Groups



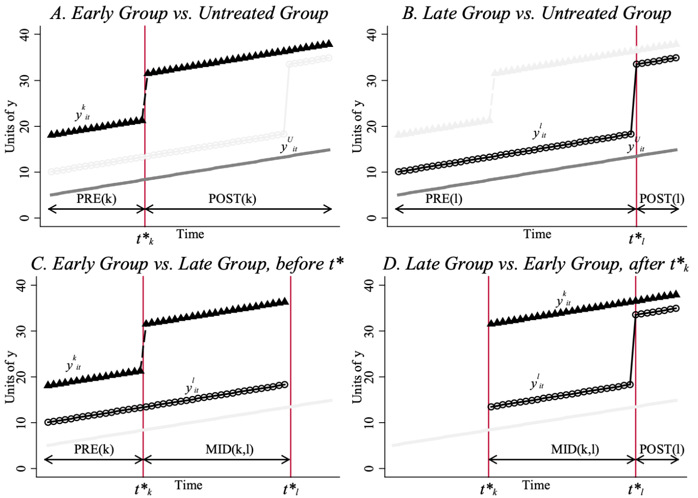
Staggered difference-in-differences

What does δ estimate in this case? [see Goodman-Bacon, 2021, for details]

- It is a **weighted average** of all possible 2-by-2 DiD estimators that compare timing groups to each other
  - Some use treated units as treatment group and untreated units as control group
  - Some use later-treated units as control (before treatment occurs) and early-treated as treatment
  - Some use early-treated as control (after treatment occurs) and later-treated as treatment
- Weights are proportional to group sizes and the variance of the treatment dummy in each pair

Staggered difference-in-differences

Figure 2. The Four Simple (2x2) Difference-in-Differences Estimates from the Three Group Case



Application – The Child Penalty

Are gender inequality and fertility linked?

How much of gender inequality can be explained by children?

- The child penalty (aka the motherhood penalty): The causal impact of having children on the outcomes of women relative to men
- Questions:
  - How do we estimate the child penalty?
  - How large is it?
  - How does it vary across time and space?
  - What are the underlying determinants?

Application # 1 – Kleven, Landais, Søgaard (2019)

The paper provides estimates of the child penalty using detailed administrative data for Denmark

Long-run child penalty – difference in labor earnings between mothers and fathers 10/20 years after birth of first child

Decomposition of the child penalty into

- **changes in participation** – extensive margin of labor supply
- **changes in hours worked** – intensive margin of labor supply
- **changes in wage rates**

Application # 1 – Kleven, Landais, Søgaard (2019)

Empirical strategy

- Event study around childbirth for fathers and mothers. Regression:

$$Y_{ist}^{g} = \underbrace{\sum_{j \neq -1} \alpha_j^g \cdot \mathbf{1}(j = t)}_{\text{event time dummies}} + \underbrace{\sum_{k} \beta_k^g \cdot \mathbf{1}(\text{age} = is)}_{\text{age dummies}} + \underbrace{\sum_{y} \gamma_y^g \cdot \mathbf{1}(y = s)}_{\text{year dummies}} + \nu_{ist}^g$$

- Regression is estimated separately for men and women with $t \in (-5, \ldots, 10)$ (i.e., between 5 years prior to childbirth until 10 years after)

- Child penalty at event time t

$$P_t \equiv \frac{\hat{\alpha}_t^m - \hat{\alpha}_t^w}{E[\widetilde{Y}_{ist}^w | t]}$$

$\rightarrow$ difference in event study coefficients for men (m) and women (w) divided by the predicted outcome when omitting the contribution of the event dummies, i.e. $\widetilde{Y}_{ist}^g = \sum_k \widehat{\beta}_k^g \cdot 1(\text{age} = is) + \sum_y \gamma_y^g \cdot 1(y = s)$

$\rightarrow$ they do so to keep the zeroes and consider both extensive and intensive margin

Data

- Administrative data on Denmark (in various spin-offs, extended to many other countries)

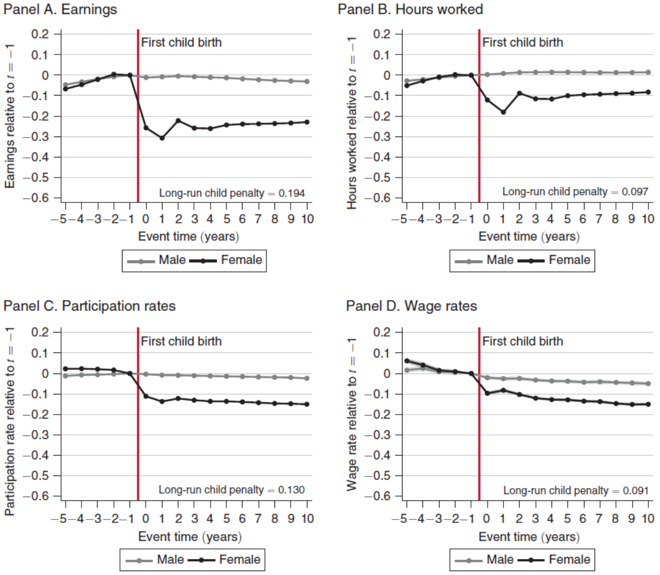
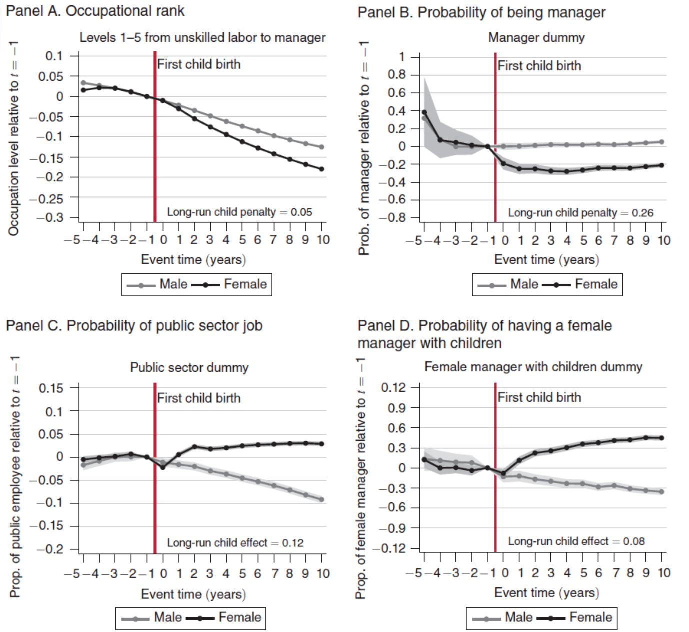


Figure 1. Impacts of Children



Panel A. Occupational rank
Levels 1–5 from unskilled labor to manager
Occupation level relative to t = −1
First child birth
Long-run child penalty = 0.05
Event time (years)
Male
Female
Panel B. Probability of being manager
Manager dummy
Prob. of manager relative to t = −1
First child birth
Long-run child penalty = 0.26
Event time (years)
Male
Female
Panel C. Probability of public sector job
Public sector dummy
Prop. of public employee relative to t = −1
First child birth
Long-run child effect = 0.12
Event time (years)
Male
Female
Panel D. Probability of having a female manager with children
Female manager with children dummy
Prop. of female manager relative to t = −1
First child birth
Long-run child effect = 0.08
Event time (years)
Male
Female

What is the contribution of children to gender inequality?

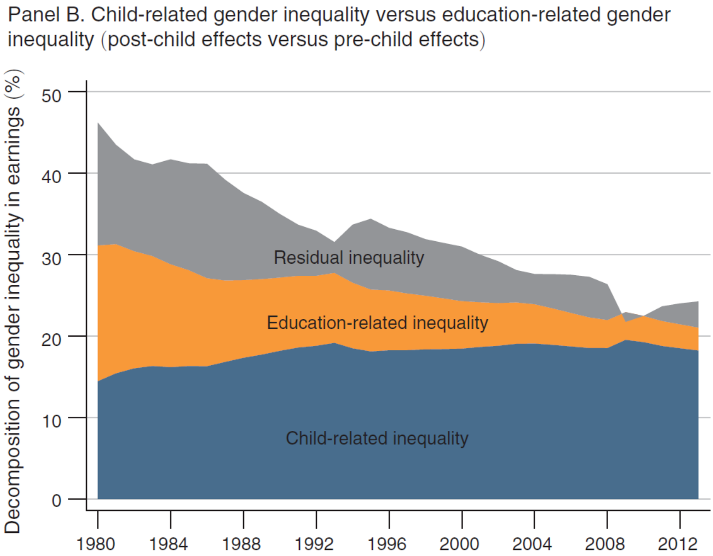
Estimate regression with year-by-event dummies and control for observables (age, education)

$$Y_{ist}^{g} = \sum_{y} \sum_{j \neq -1} \alpha_{yj}^{g} \cdot 1(j = t) \cdot 1(y = s) + \sum_{k} \beta_{k}^{g} X_{kis}^{g} + \nu_{ist}^{g}$$

Define $\Delta_s \equiv \{E[Y_{ist}^m - Y_{ist}^w]\} / E[Y_{ist}^w]$ the gender pay gap in year s. Then:

$$\hat{\Delta}_s = \underbrace{\frac{E\left[P_{st}\tilde{Y}_{ist}^{w}|s\right]}{E\left[\hat{Y}_{ist}^{m}|s\right]}}_{\text{child penalties}} + \underbrace{\frac{\sum_k \left(\hat{\beta}_k^m - \hat{\beta}_k^w\right) E\left[X_{kis}^m|s\right]}{E\left[\hat{Y}_{ist}^{m}|s\right]}}_{\text{different returns to } X\text{s}} + \underbrace{\frac{\sum_k \hat{\beta}_k^w \{E\left[X_{kis}^m\right] - E\left[X_{kis}^w\right]\}}{E\left[\hat{Y}_{ist}^{m}|s\right]}}_{\text{differences in } X\text{s}}$$

What is the contribution of children to gender inequality?



What explains the child penalty?

Culture?

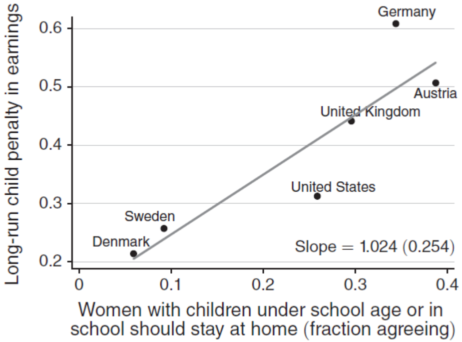


FIGURE 4. ESTIMATED CHILD PENALTIES VERSUS ELICITED GENDER NORMS

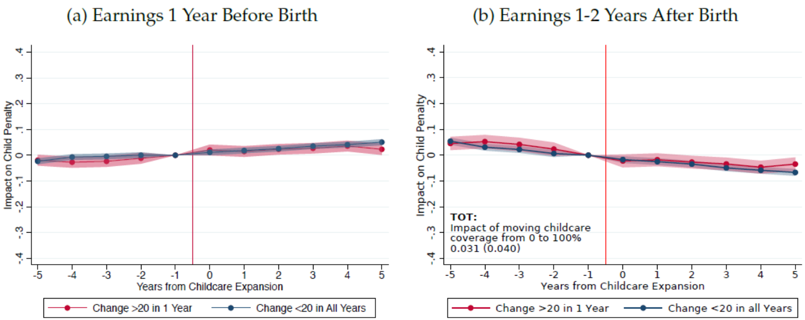
In more gender conservative countries the child penalty is larger

What explains the child penalty?

Childcare availability?

Figure 9: Estimated Effects of Nursery Care Expansions

Difference-in-Differences Evidence



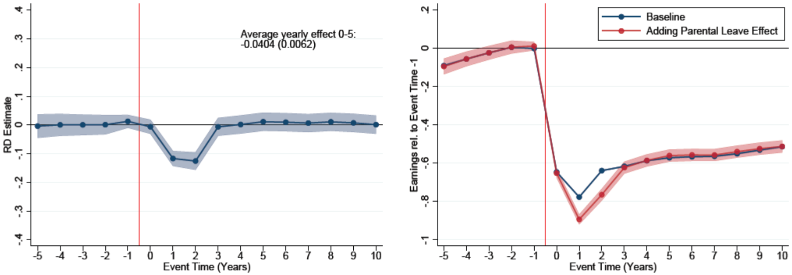
- No significant effects of childcare expansion in Austria (Kleven et al., 2021)

What explains the child penalty?

Parental leave length?

Figure 3: Parental Leave Reforms: Dynamic RD Estimates & Causal Effects on Child Penalties

(a) 1990 Reform: Dynamic RD Estimates (b) 1990 Reform: Effects on Child Penalties



- Short-run effects of parental leave expansion in Austria (Kleven et al., 2021)

Application # 2 – Casarico and Lattanzio (2021)

Research questions

- Provide evidence on the short- and long-run impact of motherhood on female labour market outcomes for Italy
- Study sorting of women with and without children across different types of firms after childbirth and assess the firm contribution to child penalties
- Investigate the individual-level, firm-level and cultural factors, which reinforce/mitigate the child penalty

Application # 2 – Casarico and Lattanzio (2023)

Data

- Social security matched employer-employee administrative data (LoSaI) – 1985-2018
- Data contains information
  - on labour contracts (annual earnings, weeks worked, full-/part-time, occupation)
  - on workers' characteristics (gender, birth year, region of residence)
  - crucially, on when female workers take maternity leave
- Maternity leave: mandatory duration of 5 months; can be taken 1 to 2 months before childbirth

Application # 2 – Casarico and Lattanzio (2023)

Empirical strategy

- Focus on working women, birth cohorts 1945-78, 18-55 years old, with age at childbirth between 18-40
- We use information on maternity leave as a proxy for first childbirth
- We build a sample of placebo non-mothers:
  - Women born between 1945 and 1978 who did not take any leave between 1985 and 2018
  - Assign age at birth to non-mothers by drawing from log-normal distribution of age at birth for mothers by cohort and quartiles of AKM worker effects
    Details AKM

Empirical strategy cont'd

- Event study around childbirth comparing labour market outcomes for mothers ($G(i) = M$) and placebo non-mothers ($G(i) = N$)

$$y_{its}^{G(i)} = \alpha_i + \sum_{k \neq -1} \beta_k^{G(i)} \cdot \mathbf{1}(k = s) + \sum_y \gamma_y^{G(i)} \cdot \mathbf{1}(y = t) + \varepsilon_{its}^{G(i)},$$

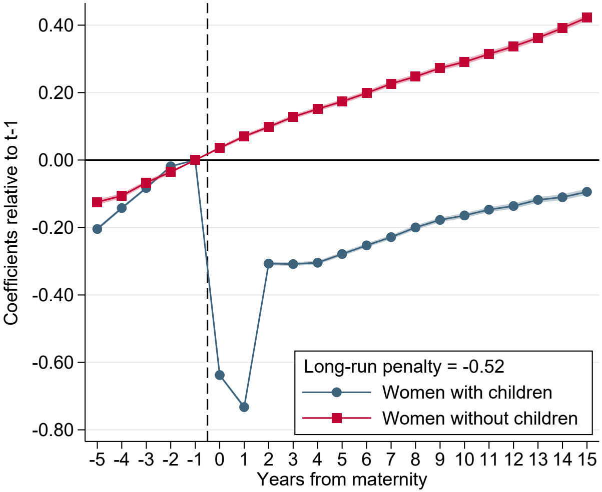
  where

  - α_i: individual fixed effects
  - $\sum_{k \neq -1} \mathbf{1}(k = s)$: event time dummies, $k = \{-5, ..., 15\}$
  - $\sum_y \mathbf{1}(y = t)$: year dummies, $t = 1985, ..., 2018$
  - $\varepsilon_{its}^{G(i)}$: error term

- Long-run child penalty $= \beta_{15}^M - \beta_{15}^N$

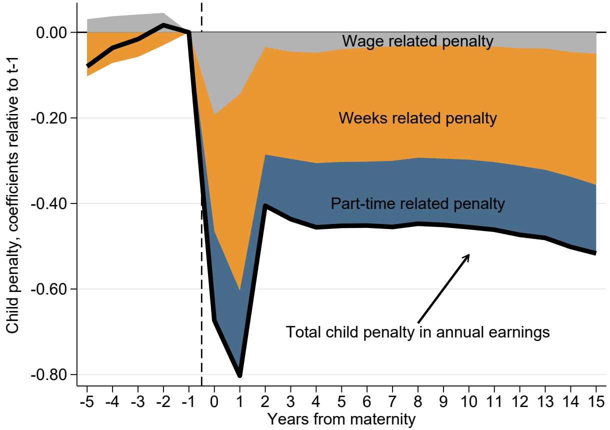
Results

Log annual earnings



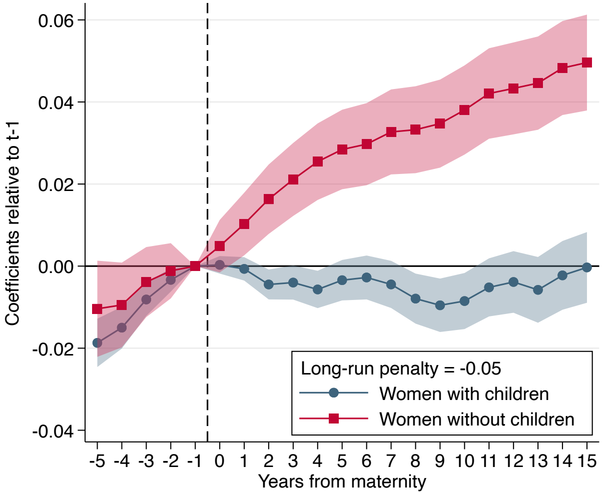
Results

Decomposition



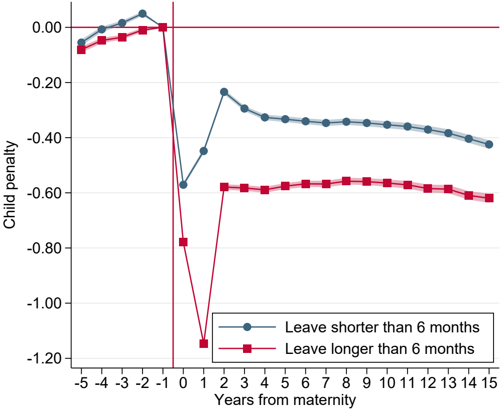
Results

Sorting - Log value added per worker

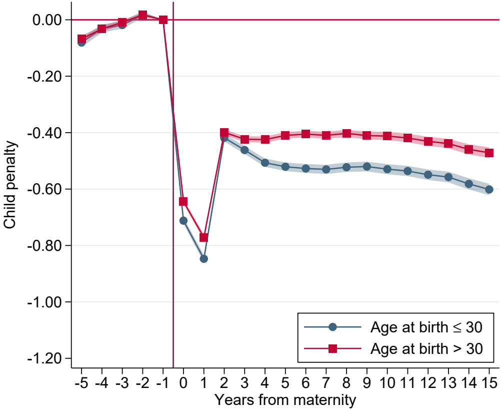


Child penalty in log annual earnings

By worker characteristics



(a) By leave duration

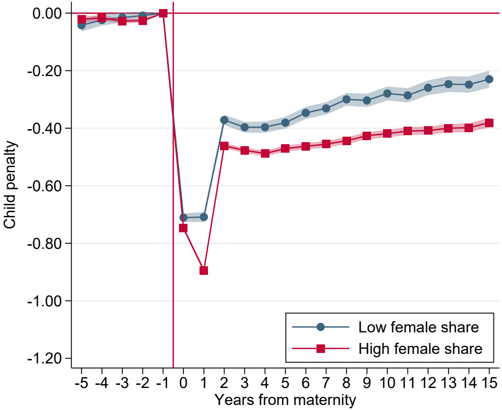


(b) By age at birth

Child penalty in log annual earnings

By firm characteristics

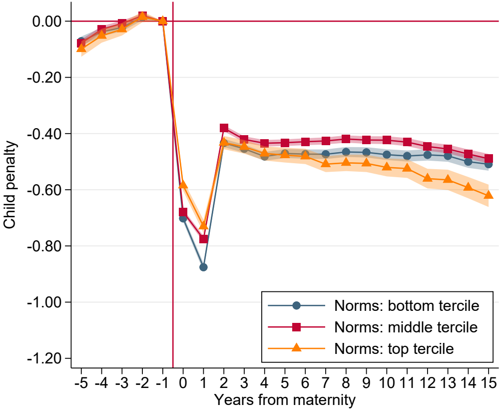
(a) By AKM firm effect



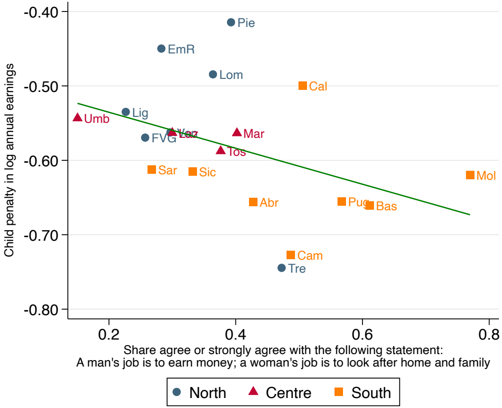
(b) By female share at the firm

Child penalty in log annual earnings

By cultural factors



(a) Event study



(b) Long-run penalty

References and Materials

*** = mandatory (only parts covered in class)**

- (*) Casarico, A., and Lattanzio, S. (2023). Behind the Child Penalty: What Contributes to the Labour Market Costs of Motherhood. *Journal of Population Economics*, 36, 1489-1511.

- Cunningham, S. "The Mixtape", Ch. 9, `https://mixtape.scunning.com/09-difference_in_differences`

- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254-277

- (*) Kleven, H., Landais, C., and Søgaard, J. E. (2019). Children and Gender Inequality: Evidence from Denmark. *American Economic Journal: Applied Economics* 11, 181-209

- Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimuller, J. (2019). Child Penalties Across Countries: Evidence and Explanations. *AEA Papers & Proceedings* 109, 122-126

- Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimuller, J. (2021). Do Family Policies Reduce Gender Inequality? Evidence from 60 Years of Policy Experimentation. *NBER Working Paper* 28082

Appendix

Placebo births

First step – identify control group of non-mothers

1. Women born in 1945-1978 (not yet 40 by 1985 and who turn 40 by 2018): those who do not have a child enter the group of never mothers
2. Assign placebo age at birth to non-mothers, by drawing from actual distribution of age at birth for mothers.

    - assume distribution of age at birth $A_{c,q} \sim \mathcal{LN}\left(\widehat{\mu}_{c,q}, \widehat{\sigma}_{c,q}\right)$, where mean $\widehat{\mu}_{c,q}$ and variance $\widehat{\sigma}_{c,q}$ are from actual distribution for mothers within cells of birth cohort c and quartiles of worker fixed effects q AKM

        $\rightarrow$ assign random draw from this distribution to actual never mothers

Back

AKM

We derive measures of workers' skills and firm pay policy from AKM worker and firm fixed effects (Abowd et al., 1999)

- Estimate the following regression over 1985-2018 on the largest connected set of male and female workers

$$w_{it} = \alpha_i + \psi_{J(i,t)} + X'_{it}\beta + \varepsilon_{it}$$

where

- w_{it}: log weekly wages of worker i in year t
- α_i: worker fixed effects
- $\psi_{J(i,t)}$: firm fixed effects
- X_{it}: cubic polynomials in age and tenure, dummies for blue- and white-collar workers, dummy for part-time workers – in levels and interacted with female dummy – and year dummies
- ε_{it}: error term

Appendix Back