Estimating Individual Level Child-penalties: Problems, Solutions, and Applications

IFAU

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CEMFI

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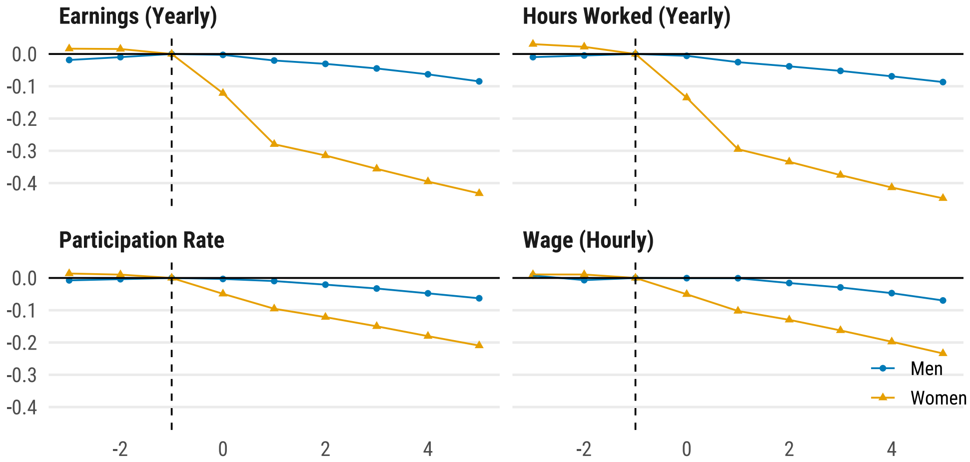
Child-penalty (CP): % earnings loss following parenthood (men vs women)



Source: Dutch Administrative Data

Rise in Child Penalty (CP) Research

- Original Kleven et al. (2019b) – 1300+ citations
  - Media: NYT, The Economist, Vox, Netflix...

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- Population average CP hides a lot of the variation
  - Important when we want to do policy evaluation on these dynamic CP measures
  - E.g., Changes in composition and selection to timing of giving birth

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Method: individual-level panel allows us to see who reacts to parental policies (Netherlands)

- Estimate individual-level event studies
- Choose your relevant aggregation level (to remove measurment error)
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Takeaways:

- Document large and meaningful heterogeneity in CP
  - E.g., CP $\approx$ 20-60% by age of giving birth
- Policy's effect on these CP measures is highly sensitive to measurement and specification
  - E.g., *qualitatevly* sensitive to selection: from -2.5% to +4%

Contribution

- **Child penalty**: women endure a big penalty post-birth, from which they never recover
  - Angelov et al. (2016); Andresen and Nix (2022); Gallen (2019); Gallen et al. (2022); Kleven et al. (2019b,a, 2022);
  - Empirical contribution:
    - Propose an individual CP measure
    - Document high heterogeneity in CP
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  - Empirical contribution:
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- **Heterogeneous two-way fixed effects**: exploring individual as opposed to aggregate effects
  - Callaway and Sant'Anna (2021); Sun and Abraham (2021); : "Forbidden comparisons" introduce bias when effects are heterogeneous
  - Borusyak et al. (2023) : Unbiased estimation for a given aggregate effect
  - Methodological contribution:
    - Individual-level event-study measurement as outcomes (beyond CP)
    - Separate the measurement and policy evaluation: allows more flexible design

Outline

How should we measure individual CP?

- Common approach – cross-sectional estimation
- Individual level child penalty
- Aggregation and decomposition (e.g., age vs cohort)

How should we evaluate the effect of child-related policies on the CP?

- Benefits – flexibility and economic interpretation of empirical design
- Comparison with common policy evaluation methods (binary treatment)

How should we measure individual CP?

Dutch Administrative Data

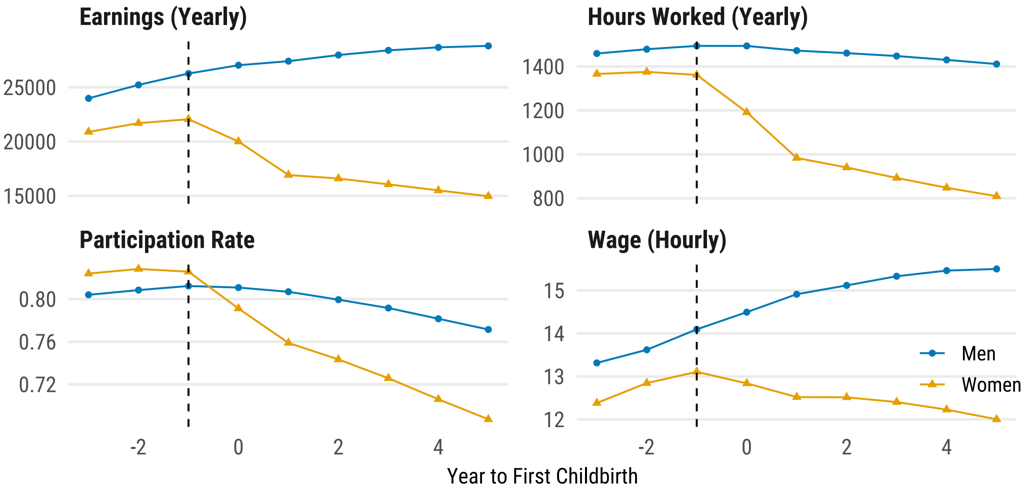
The dataset

- Tax-records: Monthly-level employer-employee dataset 1999 - 2019 (before COVID)
- Demographic data: birth year, sex, marriage/cohabitation, parent-child key
- Childcare provision records: employers of childcare service providers and their employees

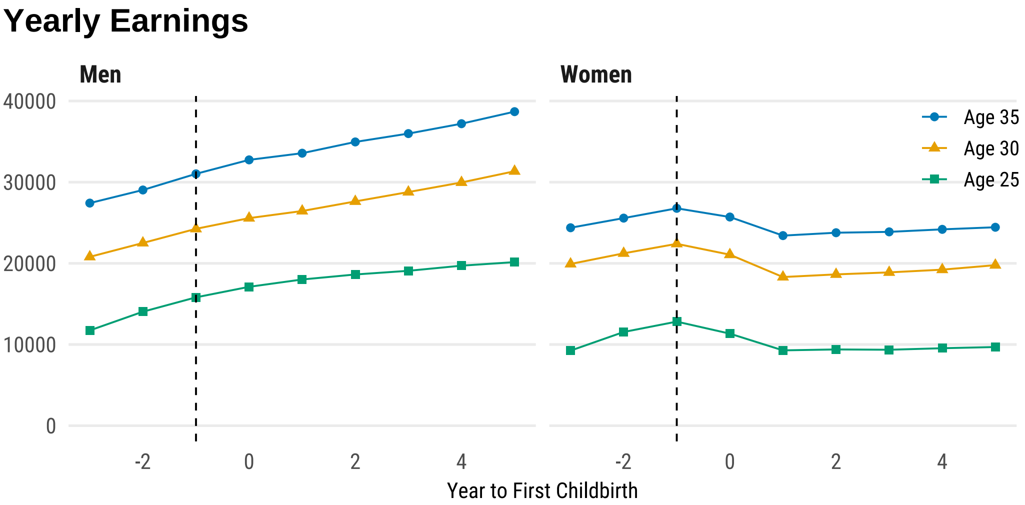
Our sample

- Birth Cohorts: 1978-1984
- Year at first childbirth: 2009-2014 (Age 25-36)
- Labor Outcomes: Years ($j = -3, \ldots, 5$) around first childbirth ($j = 0$)

Non-Normalized Child Penalty



Child Penalty by Age at First Childbirth



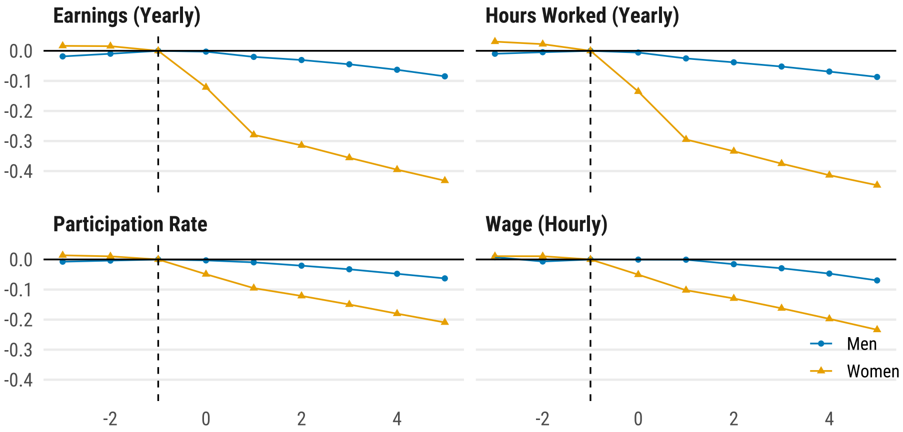
Common CP Estimation (Kleven et al., 2019b)

$$y_{it}^{g} = \alpha_{a(it)}^{g} + \lambda_{t}^{g} + \sum_{k \neq -1} \tau_{k(it)}^{g} + \nu_{it}^{g}$$

- i: individual
- t: calender year
- $k(it)$: time difference from the first childbirth
- $a(it)$: age of individual i at time t
- g: gender
- y_{it}^{g}: labor outcomes (earnings, hours worked, participation rate, hourly wage)
- ν_{it}^{g}: idiosyncratic shock

Replication of Kleven et al. (2019b) with Dutch Administrative Data

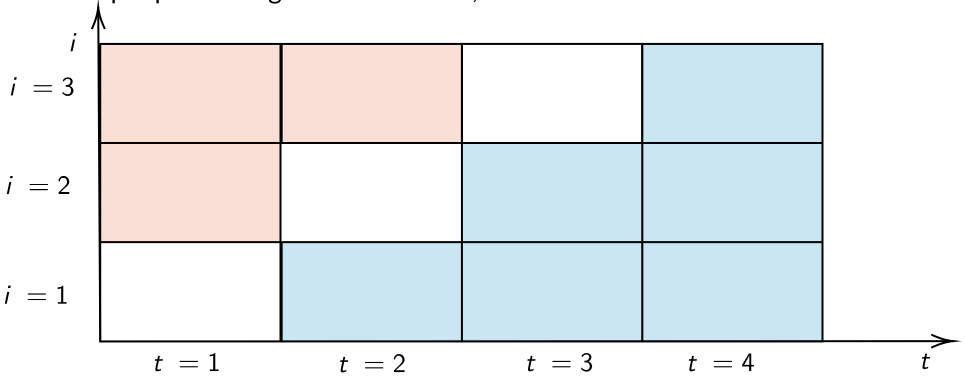
$$P_k^g := \frac{\hat{\tau}_k^g}{\frac{1}{|k|}\sum_i \sum_t \left(\hat{\alpha}_{a(it)} + \hat{\lambda}_t\right) \mathbb{1}\{k(it) = k\}}$$



Identification Illustration - Kleven et al. (2019b)

$$y_{it} = \alpha_{a(it)} + \lambda_t + \sum_{k \neq -1} \tau^{t}_{k(it)} + \nu_{it}$$

Fix birth cohort – people with age a at time $t = 1$,



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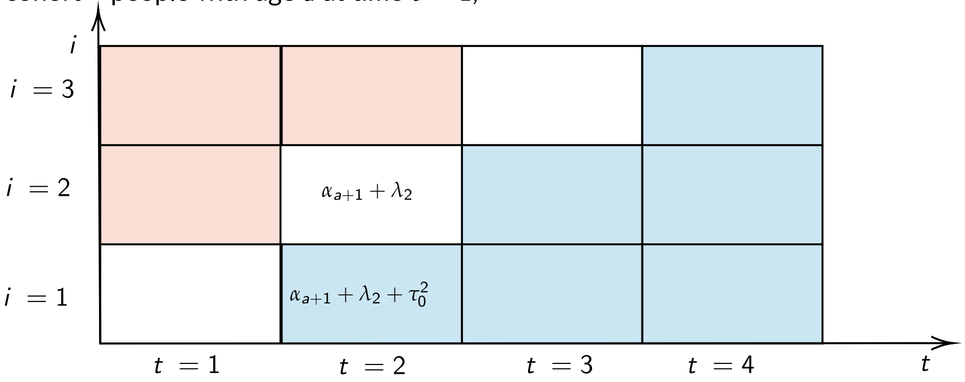

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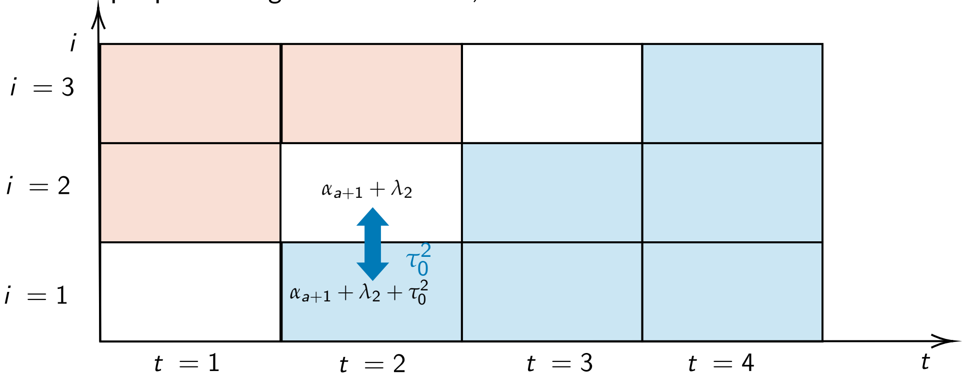

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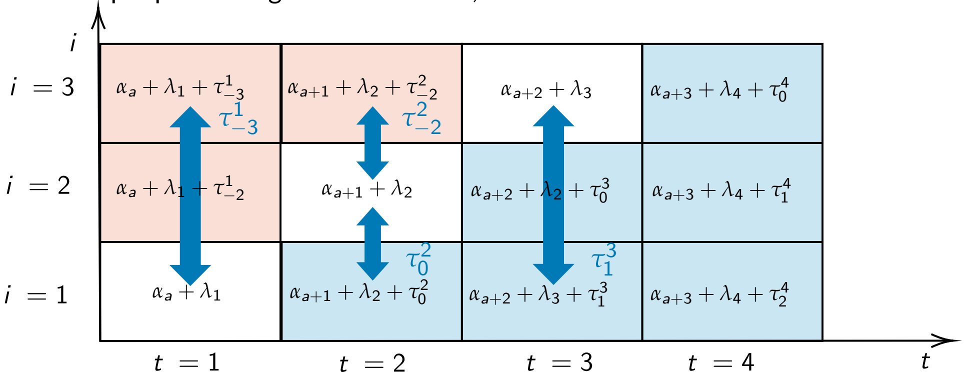

Interpretation of Common CP (Kleven et al., 2019b)

$$y_{it} = \alpha_{a(it)} + \lambda_t + \sum_{k \neq -1} \tau_{k(it)} + \nu_{it}$$

- $\tau^g_{k(it)}$ is estimated using two different types of contrasts:
  1. Within cohort/period variation across individuals who gave birth at different periods
  2. Complicated comparisons across cohorts in the same period (b/c additivity)

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- Different from usual two-way estimation (e.g., Callaway and Sant'Anna (2021)):
    1. No within-unit comparisons (cross-sectional exercise)
    2. Across cohort comparisons are tied to the particular structure between age and calendar time
    3. No need for never-treated individuals

Potential Heterogeneity and Bias in CP Estimation

- **Selection Bias:** early parenthood vs future returns to delay parenthood
- **Anticipation Effect:** reduce working hours *right* before the childbirth
- **Lifecycle Effect:** earnings increase by age, so as by relative time to the event

Individual CP: Specification

$$y_{it} = \alpha_i + \lambda_t^{g(i)} + \sum_{k \geq h} \tau_{ik} + \nu_{it}^{g}$$

- α_i: individual FE
- $\lambda_t^{g(i)}$: year FE of gender g of individual i
- $k = t - b_i$: time difference from the first childbirth
  - Note: we need at least 2 normalization periods to estimate both α_i and $\lambda_t^{g_i}$
  - Hence the no anticipation assumption – up to h periods before birth
- y_{it}: labor outcomes (earnings, hours worked, participation rate, hourly wage)
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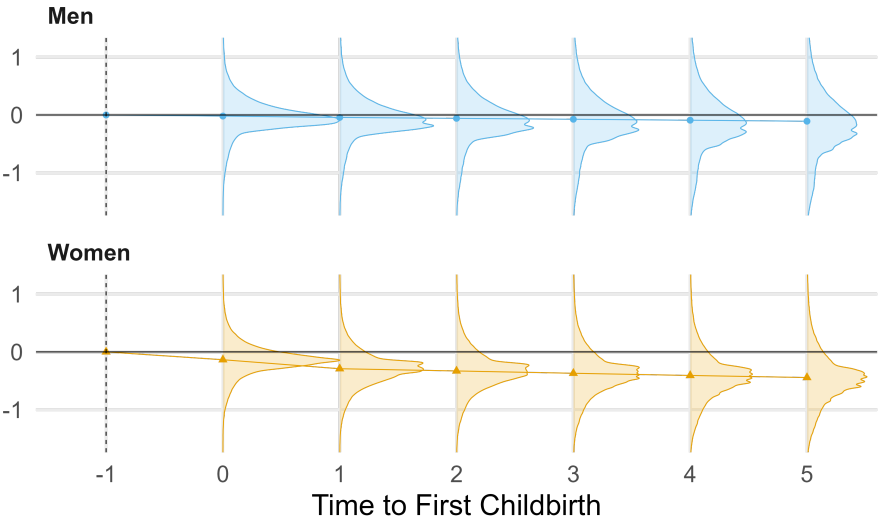
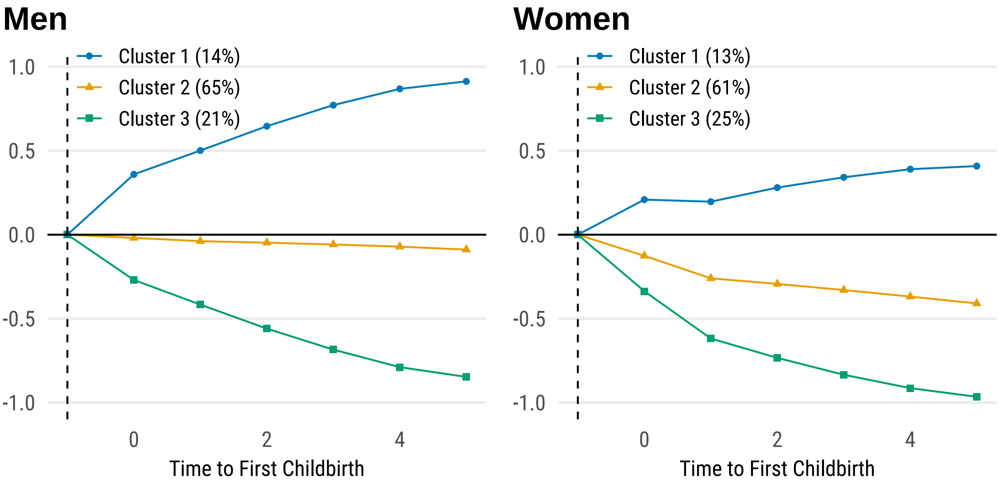
$$\tilde{\tau}_{ik} = \frac{\hat{\tau}_{ik}}{\hat{\alpha}(B_i, \tilde{A}_i) + \hat{\lambda}_t(B_i, \tilde{A}_i)}$$

High Heterogeneity in the Distribution of Individual CP



Many Different CP Paths (K-Means)



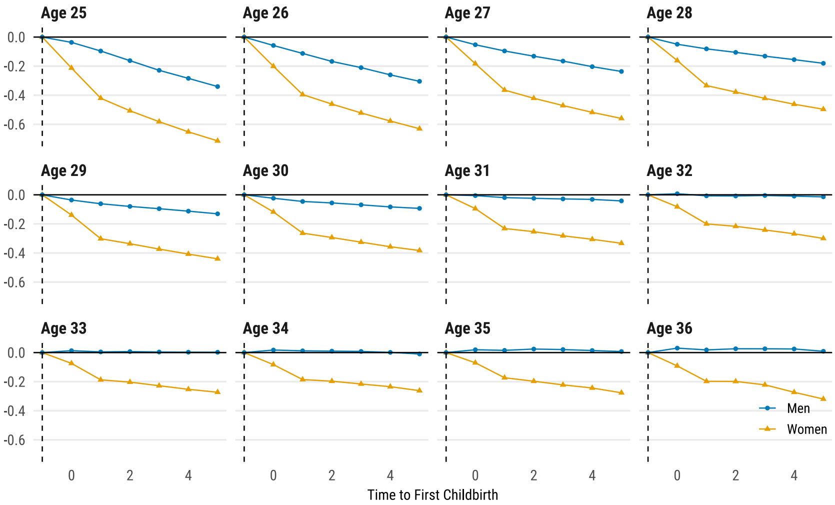
k-means explanation

Measurment Error in Individual CP Estimation

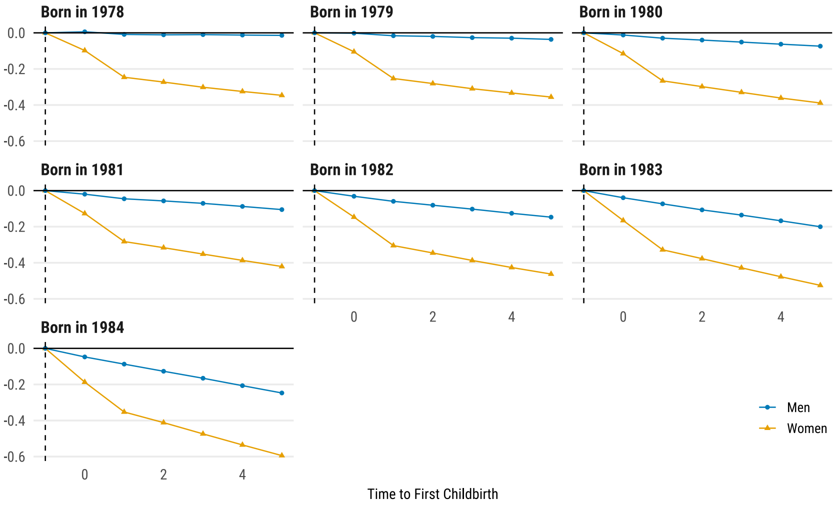
- Problem: α_i is estimated from 9 data points $\rightarrow \tau_{ik}$ has measurement error (ME)
  - ME creates attenuation bias if used as an explanatory variable
  - Still, the estimator is unbiased for conditional mean $\rightarrow$ can be used as an outcome variable
  - But not for other distributional objects (e.g., qunatiles)
- To reduce ME, can aggregate to any desired level:
  - E.g., age of first birth $(\tilde{a})$:

$$\tilde{\tau}_k(\tilde{a}) \equiv \frac{\sum \tilde{\tau}_{ik}(\tilde{a}_i = \tilde{a})}{N_{\tilde{a}}}$$

Aggregation by Age at First Childbirth



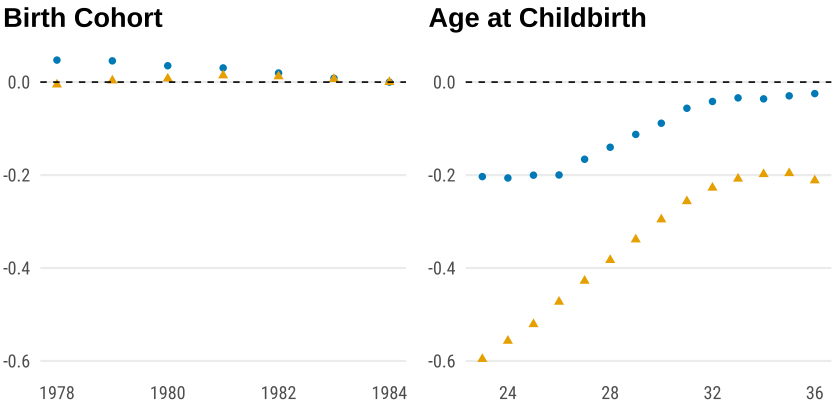
Aggregation by Birth Cohort



Decomposition

Avg. CP Decomposition: Birth Cohort vs Age at First Childbirth

$$\bar{\tau}_i = \beta_b\{b_i = b\} + \gamma_a\{\tilde{a}_i = a\} + \xi_i \qquad \text{where} \quad \bar{\tau}_i \equiv \frac{1}{K-h}\sum_{k \geq h}^{K} \tilde{\tau}_{ik}$$



Back

Taking Stock: Individual CP Estimation

- Mean CP estimation averages across cross-sections
  - Subject to: selection bias, anticipation, and lifecycle effects

- Masks large individual heterogeneity
  - Classify different CP paths

- Decompose CP to observables of interest
  - Age of giving birth is key to understanding CP patterns

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- **Next:** How should we evaluate the effect of child-related policies on the CP?

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Potential Benefits from Individual CP Est. in Policy Evaluation

1. Flexible empirical design
    - ▷ Continuous treatment
    - ▷ Flexible controls
    - ▷ Economic interpretation – elasticity

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1. Flexible empirical design
   - Continuous treatment
   - Flexible controls
   - Economic interpretation – elasticity

2. Binary treatment – comparison with common policy evaluation
   - Common strategy – estimate CP in one regression:
     - Transform a continuous treatment to binary (T indicator)
     - Transform staggered treatment to binary (POST indicator)
   - Face aggregation issues (a la 2WFE lit.)
     - Complicated regression – hard to flexibly add controls
   - Difference in sample selection

Netherlands' Childcare Expansion Reforms at 2005

Before 2005

- Childcare services were subsidized at different rates by municipalities
- Heterogeneous accountabilities of childcare services across municipalities

After 2005

- Childcare services are unified and subsidized at the same rate by the central government
- Childcare accountabilities are improved

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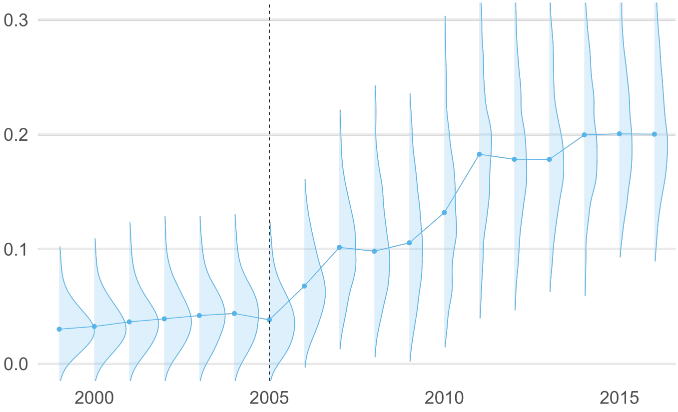
Childcare expansion and CP – mixed evidence

- Norway (Andresen and Nix, 2022) $\rightarrow$ A year of publicly provided childcare reduces CP by 23%
- Austria (Kleven et al., 2022) $\rightarrow$ A limited effect of childcare expansion on CP
- Rabaté and Rellstab (2021) study for the same reform in the Netherlands
  - A limited effect of childcare expansion on CP

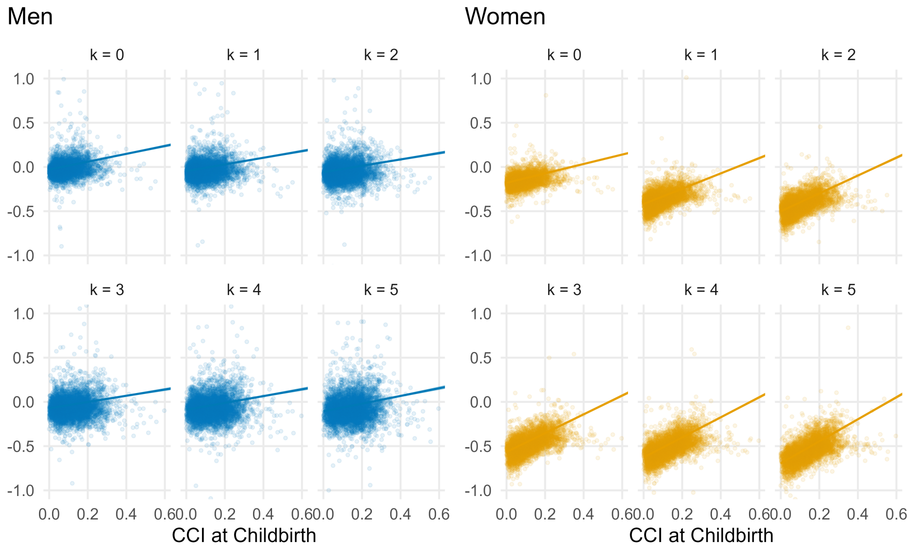
Childcare Index by Municipality (m)

$$\text{Childcare Index}_m = \frac{\text{Number of Childcare Jobs}_m}{\text{Number of Children}_m}$$



1. Flexibility and economic interpretation of empirical design

Childcare Provision Levels are Correlated with Lower CP



Linear Treatment – Elasticity of Childcare and Labor Supply

$$\text{Ave. CP}_i = \beta \cdot \text{Childcare Index}_{m(i),\tilde{t}(i)} + \alpha_{m(i)} + \lambda_{\tilde{t}(i)} + \gamma_{\tilde{a}(i)} + \varepsilon_i$$

- Ave. CP_i of individual i: $\bar{\tau}_i = \sum_{k=0}^{5} \tilde{\tau}_{ik}$
- Childcare $\text{Index}_{m(i),\tilde{t}(i)}$: childcare index of municipality $m(i)$ at the time of giving birth $\tilde{t}(i)$
- $\mu_{m(i)}$: municipality FE at the time of giving birth
- $\lambda_{\tilde{t}(i)}$: year FE at the time of giving birth
- $\alpha_{\tilde{a}(i)}$: FE of age of giving birth

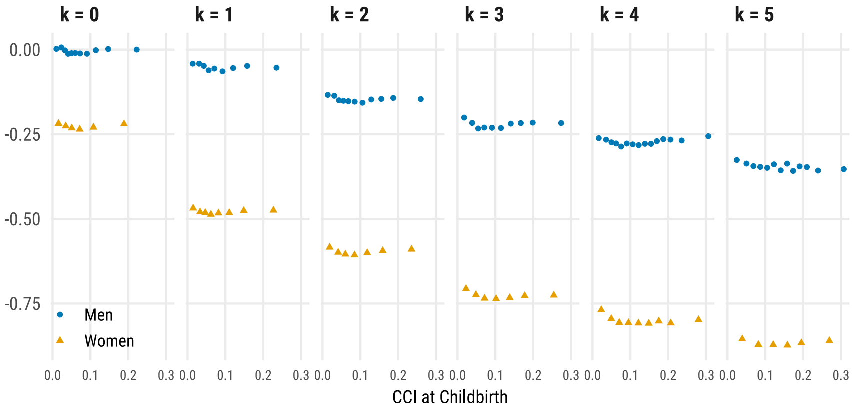
Low Elasticity of Childcare Provision and Earnings

	Men		Women	
	CP in Earnings	CP in Participation	CP in Earnings	CP in Participation
Childcare Index	0.076	-0.032+	0.183+	0.091
	(0.046)	(0.017)	(0.096)	(0.051)
Observations	735586	735586	687335	687335
R^2	0.11	0.01	0.03	0.01
FE: Year at Birth	X	X	X	X
FE: Age at Birth	X	X	X	X
FE: Municipality	X	X	X	X

$**p < .01; *p < .05; +p < .1$. Standard errors are clustered by year and municipality at birth.

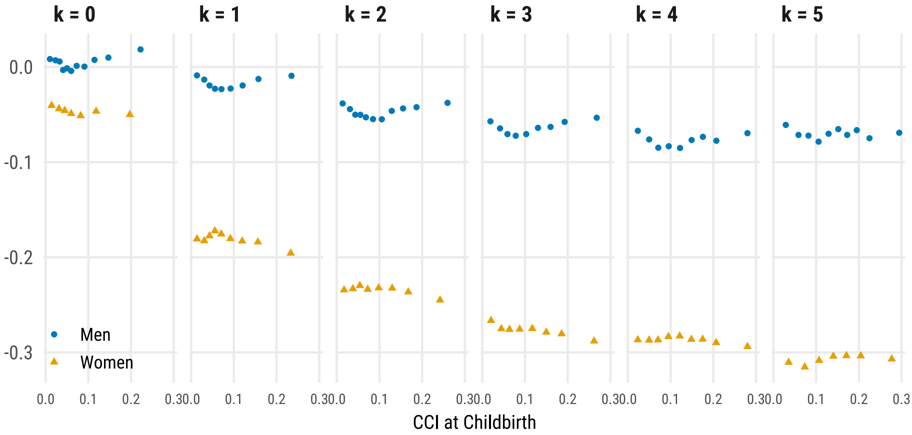
Non-parametric Treatment-effect Estimation of CCI on Earnings

$$\bar{\tau}^k_{m,\tilde{t},\tilde{a}} \sim f\left(CCI_{m,\tilde{t}}\right) + \alpha_m + \lambda_{\tilde{t}} + \gamma_{\tilde{a}}$$



Participation No age controls

Non-linear Relationship with Fathers' Labor Force Participation



No Age FE

Taking Stock: Using Individual Event-studies as Outcomes

- Effect of childcare expansion on the CP:
  - Childcare provision levels are correlated with lower CP
  - Low elasticity of childcare provision and earnings (sensitive to specification)
  - Non-linear effect on fathers' labor supply

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- Beyond the CP: any event-study measurement as outcomes
  - Can apply this flexible method to study the effects of any treatment (even continuous)
    - Our package is coming out soon to help practitioners do so

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- Beyond the CP: any event-study measurement as outcomes
  - Can apply this flexible method to study the effects of any treatment (even continuous)
    - Our package is coming out soon to help practitioners do so
  - However, other "dynamic" policy evaluations discretise their treatment effects and time variation, throwing away a lot of the variation in the data

2. Comparison with common policy evaluation methods (binary treatment)

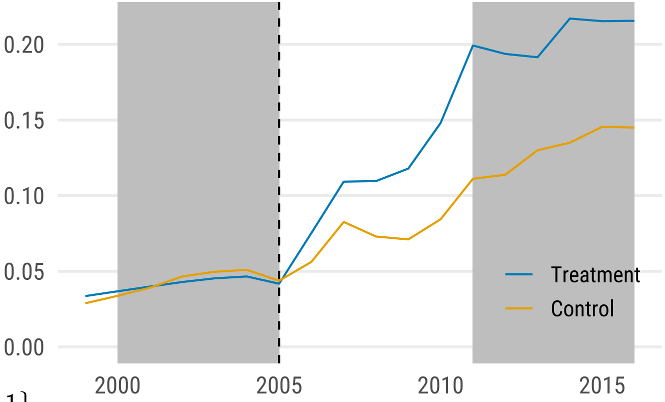
A Simple 2×2 DID Analysis

Discretise **Pre-** and **Post**-periods:

- **Pre**: gave birth in 2000
- **Post**: gave birth in 2011

Discretise **Treatment**:

$$T_m \equiv \mathbf{1}\{\overline{CCI}_m^{2011-2016} - \overline{CCI}_m^{2000-2005} > 0.1\}$$



Average Childcare Index

An Equivalent Binary Specification

Step 1: Estimate τ_{ik}

$$y_{it} = \alpha_i + \lambda_t + \gamma_{b(i)} + \mu_{r(m(i,t))} + \sum_{k\geq 0} \tau_{ik} \{E_i + k = t\} + \varepsilon_{it}$$

- $m(i,t)$: Municipality m where individual i lived at time t
- $\gamma_{b(i)}$: Fixed effect of birth cohort
- $\mu_{r(m(i,t))}$: Fixed effect of Treatment/Control group that municipality m belongs to

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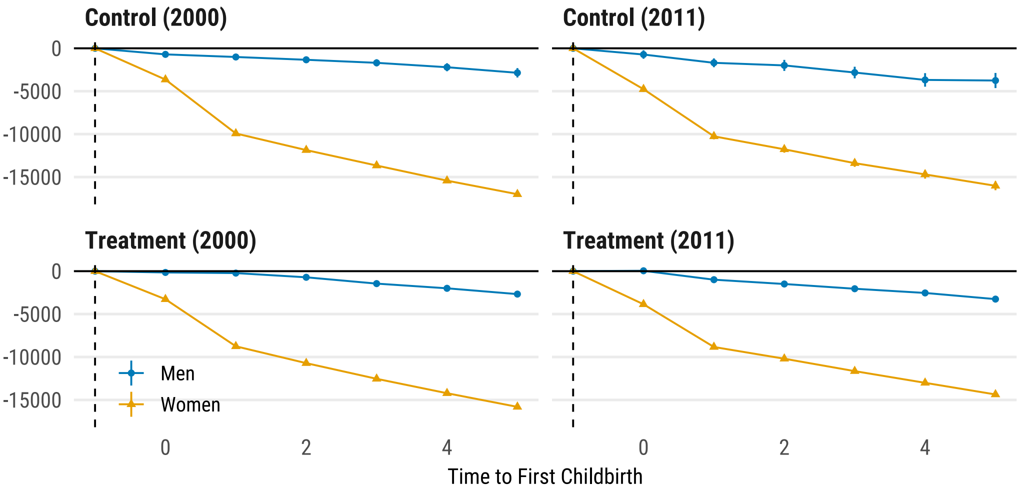
Step 2: DID on τ_{ik}

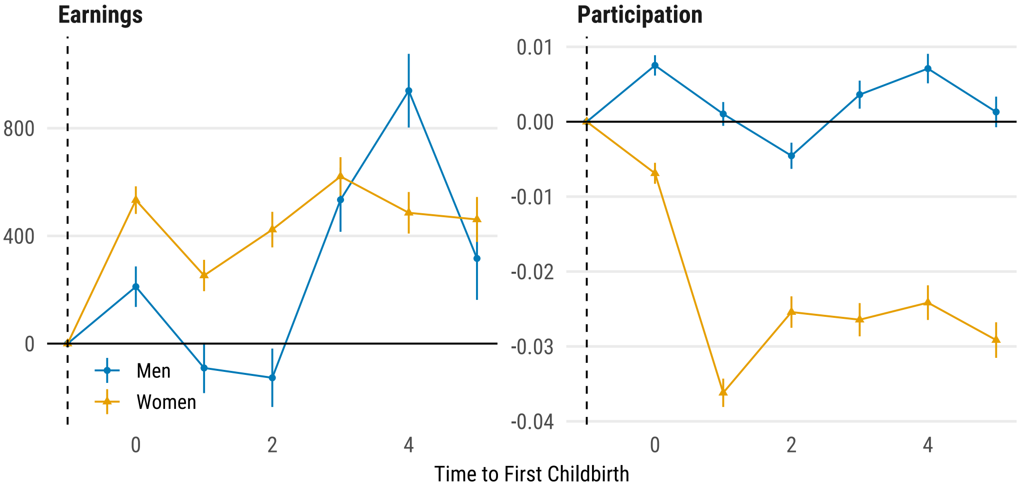
- Restrict the sample to those who gave birth in 2000 and 2011 at age 25-35
- Aggregate τ_{ik} by Treatment/Control, and Pre/Post
- Compute DID estimator for each k

CP by Treatment and Post Status



Participation

Binary Treatment – *Decrease* in FLFP?



Binary Treatment – Comparison w/ Common Specification

Our Specification

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- Step 1: Birth Cohorts 1965-1986, who gave birth until 2021
- Step 2: People who gave birth in 2000 and 2011 at age 25-35

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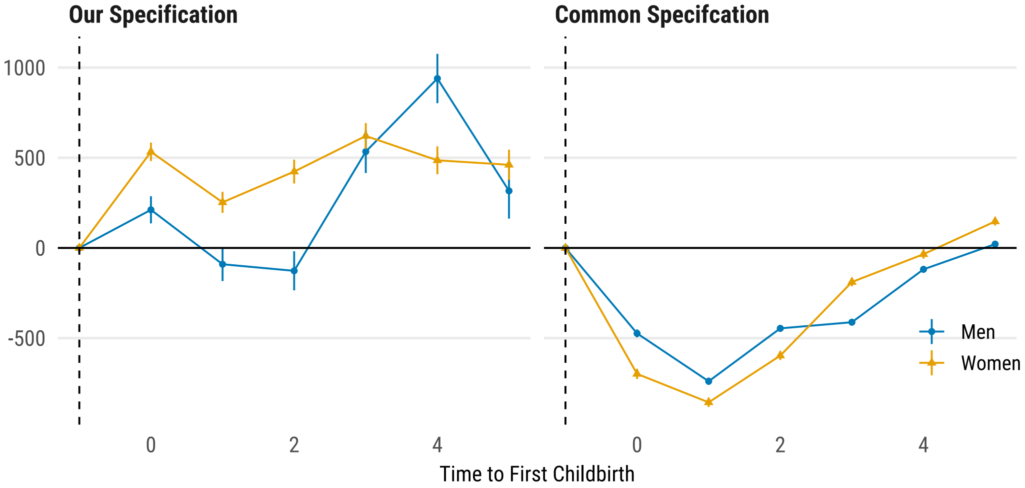
Common Specification

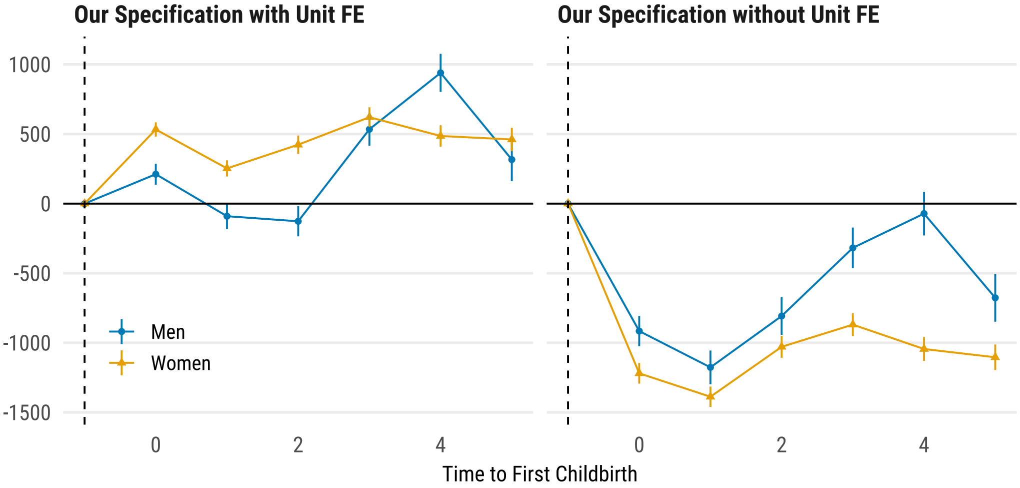
$$\begin{aligned} y_{it} &= \lambda_t + \gamma_{b(i)} + \mu_{r(m(i,t))} \\ &+ \sum_{k \neq -1} \rho_k \{E_i + k = t\} + \sum_{k \neq -1} \rho_k \{E_i + k = t\} \{\text{Treatment}\} \\ &+ \sum_{k \neq -1} \rho_k \{E_i + k = t\} \{\text{Post}\} + \delta_k \{E_i + k = t\} \{\text{Post X Treatment}\} + \varepsilon_{it} \end{aligned}$$

- Sample period: 2000-2005 and 2011-2016 – less data for CP est.
- Sample individuals: Those who gave birth at age 25-35 – unbalanced

Large *Qualitative* Differences w/ Common Policy Evaluation



Large Differences due to Downward Selection Bias (Unit FE)



Conclusion: New Method to Est. Individual CP for Policy Evaluation

- Document large and meaningful heterogeneity in CP
  - Different CP paths
  - CP $\approx$ 20-60% by age of giving birth

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- Policy's effect on these CP measures is highly sensitive to measurement and specification
  - Individual CP estimation allows for flexible & economically interperable design
  - Common specification is sensitive to selection bias: from -2.5% to +4%

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- Stay tuned for...
  - Intergenerational mobility in CP
  - Other moments: quantile treatment effects (correction on error term)

THE END!

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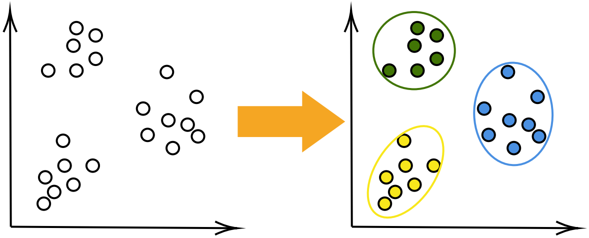
Appendix

K-means on $\hat{\tau}_{ik}$

K-means is a classification method of points



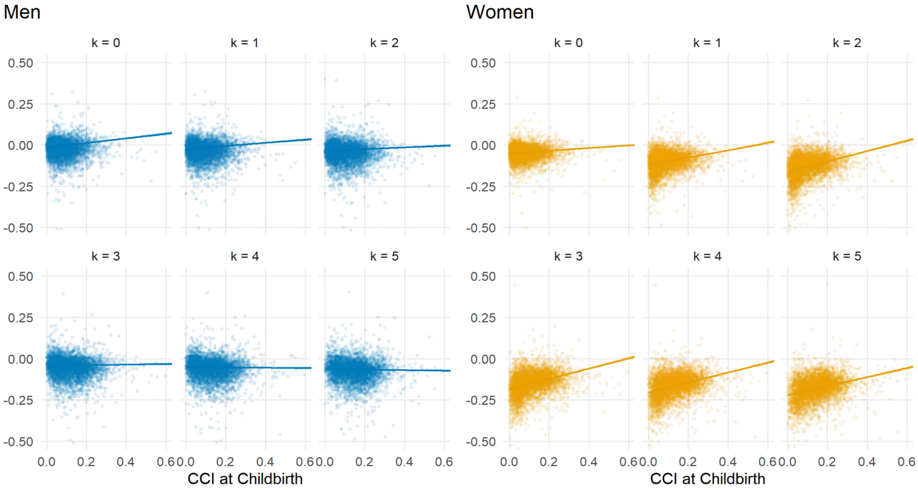
After the estimation on τ_{ik}, we have for each individual i,

$$\hat{\boldsymbol{\tau}}_i = (\hat{\tau}_{i0}, \dots, \hat{\tau}_{i5}).$$

We classify $\{\hat{\boldsymbol{\tau}}_i, \dots, \hat{\boldsymbol{\tau}_N}\}$ into 3 clusters by K-means.

k-means estimation

Childcare Provision Levels are Correlated w/ Lower CP



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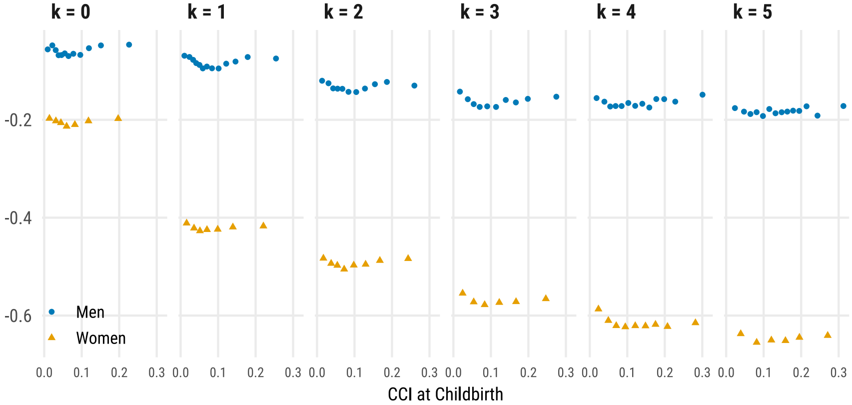
Non-parametric Treatment Effects on Earnings (No Age FE)

$$\bar{\tau}^k_{m,\tilde{t}} \sim \alpha_m + \lambda_{\tilde{t}} + f(CCI_{m,\tilde{t}})$$



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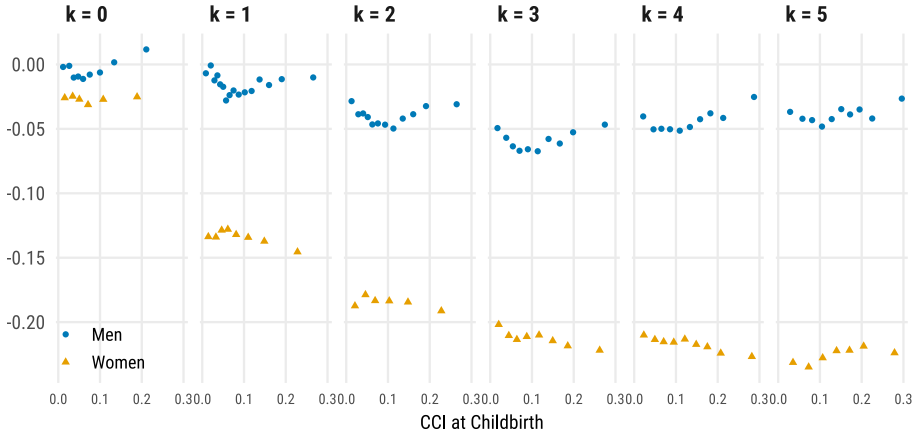
Non-parametric Treatment Effects on Participation (No Age FE)



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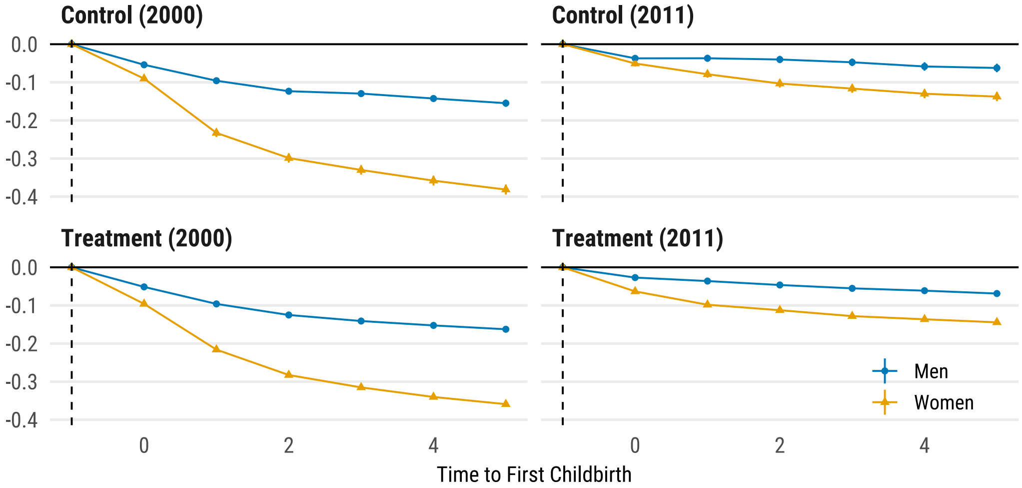
CP by Treatment and Post Status (Childcare Expansion)



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