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DISCUSSION PAPER SERIES

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Renren Gan
Leiden University

Egbert Jongen
Leiden University, CESifo, IFS and IZA

Simon Rabaté
CPB, INED and IZA

Bo Terpstra
Leiden University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Evolution of the Child Penalty and Gender-Related Inequality in the Netherlands, 1989-2022*

We study the evolution of the child penalty and gender-related inequality in the Netherlands. We use administrative panel data from 1989 to 2022 in an extension of the event study approach used in Kleven et al. (2019b). We document a substantial decline in child penalties (in earnings) for first-time mothers from 60% in the early 1990s to 35% in the 2010s. This decline is much larger than in the handful of other countries documented so far. However, looking at subperiods, we also find that the decline in the child penalty in the Netherlands has stalled in the mid 2000s, despite a steep rise in spending on formal childcare. Next, we decompose the gender-related inequality for parents into inequality related to children, education, migration background and a residual. We find that overall gender-related inequality and child-related gender inequality decline in parallel over time. The role of education and migration background is small and becomes less important over time. Hence, a substantial residual remains, and cannot be attributed to the aforementioned factors. We also show that the event-time window used is crucial for the contribution of the child penalty to the evolution of gender inequality.

JEL Classification: D63, J13, J16
Keywords: child penalty, gender-related inequality, evolution

Corresponding author:
Egbert Jongen
Leiden University
Faculty of Law
Department of Economics
Steenschuur 25
2311 ES Leiden
The Netherlands

E-mail: e.l.w.jongen@law.leidenuniv.nl

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1 Introduction

Gender inequality in earnings and other labor market outcomes is an important topic in academia and the policy debate. While economically advanced countries have seen substantial gender convergence in labor market outcomes, progress appears to have slowed down considerably over the past two decades (Blau and Kahn, 2008; Goldin, 2014; Blau and Kahn, 2017).[1] The earlier literature often focuses on the role of human capital, such as education, to explain gender disparities. However, since the 1980s, the gender gap in education has substantially narrowed or even disappeared in advanced economies (Goldin et al., 2006; McDaniel, 2010).[2] In contrast, the unexplained portion of the gender gap has stabilized following a significant decline (Blau and Kahn, 2017). Meanwhile, the share of gender inequality attributable to childbearing appears to have become more important over time (Kleven et al., 2019b; Cortés and Pan, 2023; Glogowsky et al., 2025).

A growing body of research quantifies the impact of children on labor market outcomes. One widely used approach is the event study methodology proposed by Kleven et al. (2019b), which defines the child penalty as the effect of the first child on labor market outcomes for mothers and fathers. This framework has become a standard tool, facilitating child penalty comparisons across countries (Kleven et al., 2019a, 2024a) and among heterogeneous populations (Andresen and Nix, 2022; Nieto, 2021; Rellstab, 2024).[3] Several studies also consider potential determinants of the child penalty, including biological (Moberg, 2016; Kleven et al., 2021; Rosenbaum, 2021), psychological (Kuziemko et al., 2018), discriminatory (Glauber, 2018; Casarico and Lattanzio, 2023; Gallen, 2024), household decision-making (Angelov et al., 2016; Chung et al., 2017; Lundborg et al., 2017; Nieto, 2021; Casarico and Lattanzio, 2023; Cortés and Pan, 2023) and normative (Kleven et al., 2019b; Boelmann et al., 2025; Nieto, 2021; Rellstab, 2024) factors, and the role of work-and-care policies like paid leave and subsidized childcare (Rabaté and

[1] Goldin (2014) and Blau and Kahn (2017) highlight the plateau in the U.S. labor market, and World Economic Forum (2023) show its presence in Europe and North America since 2006.

[2] Rellstab (2024) already noted that also in the Netherlands, young women now outperform young men in terms of educational attainment.

[3] Child penalties across economically advanced countries are summarized in Table 1 of Rabaté and Rellstab (2022).

Rellstab, 2022; Kleven et al., 2024b; Glogowsky et al., 2025). Only a few studies so far consider the evolution of the child penalty over time (Kleven et al., 2019b; Kleven, 2022; Kleven et al., 2024b,a; Sundberg, 2024; Glogowsky et al., 2025) and the evolution of the proportion of child-related inequality in total gender-based inequality (Kleven et al., 2019b; Cortés and Pan, 2023; Kleven et al., 2024b; Glogowsky et al., 2025).[4]

In this paper we study the evolution of the child penalty in the Netherlands over the past three decades, using administrative panel data and an extended version of the event study methodology of Kleven et al. (2019b). We consider the impact of childbirth on the earnings and employment rate of women and men. Furthermore, we decompose gender-based inequality over the past three decades into child-related, education-related and migration-background-related inequality and a residual.

We extend the basic event study setup to estimate the child penalty of Kleven et al. (2019b) with interaction terms to study the child penalty by cohort, education level and migration background while making efficient use of the available data. Furthermore, we modify the Oaxaca-Blinder decomposition used in Kleven et al. (2019b) to our setup, to study the contribution of inequality resulting from children, education and migration background in the evolution of gender-based inequality over time. We use administrative panel data from the Income Panel (IPO) 1989–2022, from which we take the household composition and year of birth of all the household members, primary earnings (consisting of wage income from employment and profit income from self-employment), the employment rate and migration background.Furthermore, we merge the data on education, which has a coverage of about two thirds of the individuals in the Income Panel.[5] Our main findings are the following. First, we find a large decline in the child penalty for mothers between the 1990s and the 2010s. Specifically, first-time mothers in the 1990s faced large child penalties of 60% in earnings, and this was almost cut in half to 35% for first-time mothers in the 2010s. Employment penalties also declined, from 25% in the 1990s to 11%

[4]Employing a dynamic Oaxaca-Blinder decomposition framework, following e.g. Blau and Kahn (2017).

[5]Noting that the explanatory and outcome variables in this somewhat smaller sample are comparable to the full Income Panel, see the Data section.

in the 2010s.[6,7] For fathers, there was hardly any change in the child penalty over time, both in earnings and the employment rate. Furthermore, the child penalties for fathers are small and not statistically significantly different from zero.

Second, the decline in the child penalty occurred mostly during the 1990s and the early 2000s, but appears to have stalled in the mid 2000s. This may seem surprising, given that there was a substantial policy reform that led to a large increase in child care subsidies from the mid 2000s to the early 2010s (though there was a cut in childcare subsidies in 2012 again). However, it is consistent with differences-in-differences studies for the Netherlands that use data around this reform (Bettendorf et al., 2015; Rabaté and Rellstab, 2022), which find no or only modest effects on earnings and the employment rate.[8]

Third, we find that total gender inequality in earnings and child-related inequality in earnings decline in parallel between 1990 and 2022. The contribution of education to gender inequality is small and has disappeared over time, while the contribution of migration background to gender inequality is not much bigger and also has become smaller over time. Hence, a substantial unexplained residual remains. However, we also show that the (sometimes implicit) sample selection can be quite important for the relative contribution of child-related inequality in the decomposition gender-based inequality over time.

This paper contributes to the literature on the child penalty and gender inequality in several ways. First, methodologically, we generalize the event study framework of Kleven et al. (2019b) for estimating child penalties by incorporating categorical groupings. The framework, using all observations to estimate heterogeneous child penalties, is flexible

[6] We find that ten years after the birth of the first child, the child penalty in earnings reaches 55%, while the penalty in the employment rate is approximately 20% (we do not have data for hours worked, but Rabaté and Rellstab (2022) show that in the 2000s, the gap between the child penalty in earnings and the employment rate is predominantly the result of a child penalty in hours worked, and to a lesser extent in hourly wages).

[7] Our average child penalty is somewhat higher than those reported by Rabaté and Rellstab (2022) for the Netherlands. However, they analyzed data for the period 2002 to 2016, and we show that the child penalty has declined over time in the Netherlands. The average child penalty in the employment rate we find aligns with the Kleven et al. (2024a), which covers data from 1990 to 2018 for the Netherlands.

[8] Furthermore, it is consistent with the small and insignificant effects found by Kleven et al. (2024b) for the expansion of subsidized childcare in Austria.

when controlling for heterogeneity and efficient when the number of categories are large relative to the sample.[9] Furthermore, we extend the dynamic decomposition framework proposed by Kleven et al. (2019b) to account for the different stages following the first childbirth, and also show that the sample selection can be quite important for the contribution of child-related earnings inequality in the evolution of overall gender-related earnings inequality. In particular, when we do not restrict the event-time window, we find that child-related earnings inequality becomes the dominant factor in overall gender-based inequality and the residual becomes small, as in Kleven et al. (2019b). However, when we restrict the event-time window to 0–10 years following first-time child birth, child-related earnings inequality and overall gender-based inequality decline in parallel and a substantial residual remains. Hence, to study the contribution of child-related earnings inequality in overall gender-based inequality over time it is crucial to do an 'apples-to-apples' comparison in terms of the event-time window, which is not always done in the related literature.

Second, empirically, our study reveals trends in the child penalty and the contribution of child-related earnings inequality for the Netherlands that differ from the findings for the handful of papers that have studied these issues (in earnings[10]) so far (Kleven et al., 2019b; Kleven, 2022; Cortés and Pan, 2023; Kleven et al., 2024b; Sundberg, 2024; Glogowsky et al., 2025). Figure 1 compares our findings to these papers, for the periods as close as possible to our time window.Considering the evolution of the child penalty for mothers over time[11] in panel (a), we see that the decline in the child penalty for first-time mothers in the Netherlands is much larger than in Austria, Denmark and Sweden, whereas the child penalty in Germany even has gone up. The decline is also much larger than in the US. Regarding gender-based inequality and the role of children in panel (b), we also find

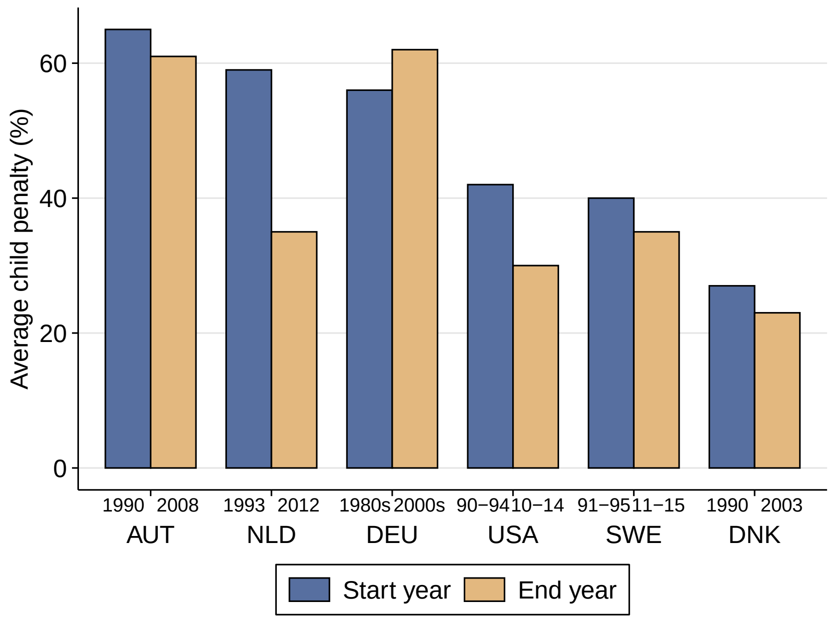
[9] As noted in, e.g., Glogowsky et al. (2025, footnote 4), there is an ongoing debate about the optimal strategy to estimate child penalties, where some yield smaller penalties and some yield larger ones. In line with Glogowsky et al. (2025) we follow the mainstream methodology that builds on Kleven et al. (2019b), which ensures that our results are comparable to the broader literature and also allows us to make some points related directly to this broader literature.

[10] Kleven et al. (2024a) considers the evolution of the child penalty in the employment rate around the world in depth. However, as we show, the level and evolution in the child penalty in earnings and the employment rate can differ quite a lot, and what we are ultimately interested in is the child penalty in earnings, which captures a variety of channels, including the employment rate.

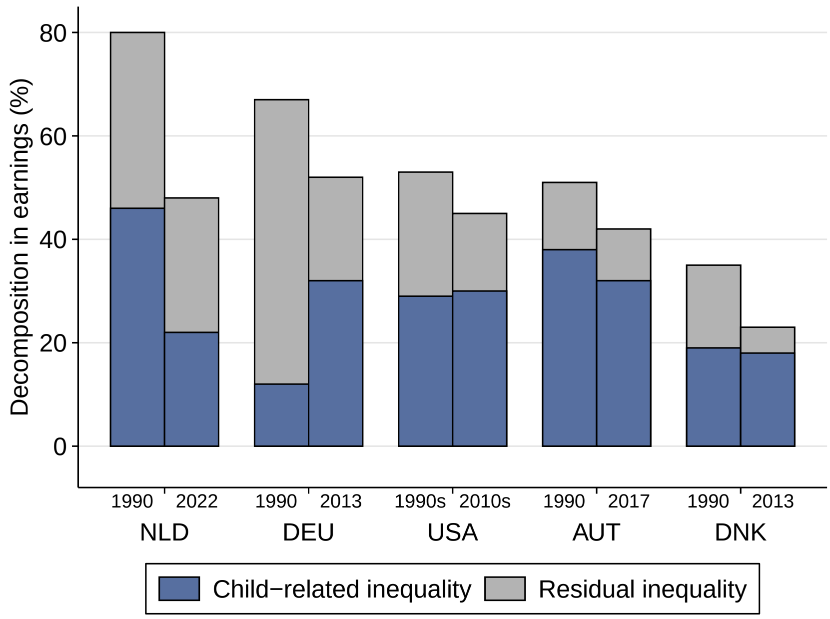
[11] The child penalty for fathers is typically small and remains small over time.

Figure 1: Evolution child penalty and contribution to gender inequality: selected studies

(a) Evolution of the child penalty of mothers



(b) Evolution gender-based and child-related inequality



Notes: Panel (a) compares our findings on the evolution of the child penalty to related papers, for the periods as close as possible to our time window. The child penalty is the average child penalty for event time 0 to 10 (up to 10 years after the birth of the first child). Panel (b) compares our findings on the evolution of gender-based inequality to related papers, again for the periods as close as possible to our time window. However, here it is important to note that the different papers consider different event time windows. An overview of these event time windows and the exact references of the findings of the other papers is given in Table A.1 in the Appendix.

a stronger decline in gender-related inequality than in the other countries, starting from a higher level. However, in contrast to the other countries, we also find a substantial decline in child-related inequality. But here the sample selection is crucial, if we do not restrict the event-time window to 0–10 years after first-child birth we also find only a limited decline in child-related inequality, as in Kleven et al. (2019b). Consistent with the findings in Kleven et al. (2019b), we find that the role of education in gender-based inequality has disappeared, and we provide robust evidence on the differences in child penalties between native and immigrant populations (Nieto, 2021).

The outline of the paper is as follows. Section 2 describes the data and provides summary statistics of the sample. Section 3 presents the empirical methodology and the results for the estimation of the child penalty, using a flexible event study framework with three specific applications, including one using first-time birth cohorts. Section 4 presents the dynamic decomposition to determine the contribution of children, education and migration background to the evolution of gender-based inequality. Section 5 concludes. An appendix contains supplementary material.

2 Data

Below we outline the datasets and the variables that we use in the empirical analysis, we discuss the construction of the sample and present summary statistics for this sample.

Datasets We use administrative microdata from Statistics Netherlands (CBS) covering the period 1989–2022.[12] The primary data source is the Income Panel (*Inkomenspanel* in Dutch), a longitudinal dataset spanning from 1977 to 2022 with the panel design beginning in 1989.[13] The Income Panel contains detailed socio-demographic information on individuals and households.[14] The Income Panel covers approximately 0.6% of the

[12]The datasets used in this study are linked and remotely accessed through a secured environment provided by Statistics Netherlands.

[13]For the period 2015–2022 the Income Panel is part of the integral income files INHATAB, where they are indicated with a weight. Furthermore, consistent with the IPO before 2015 the sample is updated every year and the weights are adjusted so that the sample remains representative of the population.

[14]For the years 2015–2022, we combine the Income Panel sample in INHATAB with the integral personal income files from INPATAB for earnings and employment, and with GBAPERSOONTAB and

population in the Netherlands (approximately 100 thousand individuals in households) and includes a household-level weight to make the sample representative of the full population (Statistics Netherlands, 2016). Additionally, we merge education data (from HOOGSTEOPLTAB) with the Income Panel. This dataset contains information on the highest achieved education level for the majority of the individuals living in the Netherlands, and covers more than 70% of individuals in the Income Panel. Below we will show that the descriptive statistics on observable characteristics are quite similar between the full Income Panel sample and the merged sample where we include the education variable.

Demographic variables We use detailed demographic information for each individual (gender, age and migration background) as well as households (household size and composition). We identify first-born children and their parents using the household composition data. Specifically, a newborn is classified as the first child in a household if, in the year of birth, the household consists of three members (a couple with a young child) or two members (a single parent with a young child).[15] Parents are then identified via a shared household identification number. Migration background is defined following the classification system used by Statistics Netherlands, based on an individual's and their parents' countries of birth. Individuals are categorized as natives, first-generation immigrants, or second-generation immigrants. First-generation immigrants are born abroad and have at least one foreign-born parent. Second-generation immigrants are born in the Netherlands but have at least one foreign-born parent. For educational background, we adopt a three-level classification system: lower, secondary, and higher education. This classification aligns with ISCED 2011 standards, where lower education corresponds to levels 0–2, secondary to levels 3–4, and higher to levels above 4.[16]

GBAHUISHOUDENBUS for the socio-demographic variables for individuals and households, respectively.

[15] As a result, twins are excluded from the definition of first-born children.

[16] In the Dutch education system, low education includes primary education (including special needs), prevocational secondary education (VMBO), secondary vocational education level 1 (MBO 1), and the first three years of senior general secondary education (HAVO) or pre-university education (VWO). Secondary education comprises the final years of HAVO or VWO and secondary vocational education levels 2–4 (MBO 2, 3, or 4). Higher education refers to higher professional education (HBO), university bachelor's or master's degrees, and doctoral programs.

Earnings and the employment rate The earnings data (adjusted to 2019 euros, using the consumer price index) refer to an individual's primary income, combining income from wages as an employee and profits from self-employment. Regarding the employment rate, we classify individuals as employed if they report any non-zero primary income, including self-employed individuals regardless of actual revenue generation. Note that this definition of employment will lead to higher employment rates than e.g. the Labor Force Survey, which uses data on employment at the time (week, or preceding week) of the interview.

Sample construction We use observations for the period 1989 to 2022, for parents who had their first child between 1979 and 2021. We restrict the sample to individuals who were between 20 and 45 years old at the time of their first child's birth. We do not impose any restrictions based on the relationship status of the parents when they had their first child; single parents are therefore included. Note that a parent can, in some cases, be linked to multiple first children. This occurs when an individual enters a new household and has a newborn child who is the first child in that household, but not their biological first child. To simplify the analysis, we exclude parents associated with more than one first child. We further construct a balanced panel by selecting parents who are continuously observed over a 14-year window surrounding the birth of their first child—that is, from four years before to ten years after childbirth.This results in 303,540 individual-year observations, covering parents whose first child was born between 1993 and 2012. For the analyses involving educational background, we restrict the balanced panel to parents with recorded education levels, yielding 208,140 observations.

Descriptive statistics Descriptive statistics of the samples with and without education for mothers and fathers are given Table 1. It is a balanced sample with 15 observations per mother and father, from 4 years before the first child birth to 10 years after. The characteristics of individuals with registered education information closely resemble those

Table 1: Descriptive statistics estimation sample

(a) Mothers

	Base sample		Sample with educ.	
	Mean	SD	Mean	SD
Age at first birth	29.868	4.053	29.759	4.127
First generation (proportion)	0.057	0.232	0.063	0.243
Second generation (proportion)	0.069	0.253	0.074	0.261
Secondary-educated (proportion)	—	—	0.422	0.494
Higher-educated (proportion)	—	—	0.429	0.495
Earnings (before)	28,497	16,600	28,527	17,287
Earnings (after)	21,786	21,156	22,864	22,247
Employment rate (before)	0.954	0.209	0.955	0.208
Employment rate (after)	0.851	0.356	0.859	0.348
Observations	154,065		108,360	

(a) Fathers

	Base sample		Sample with educ.	
	Mean	SD	Mean	SD
Age at first birth	32.245	4.300	32.161	4.257
First generation (proportion)	0.057	0.232	0.060	0.238
Second generation (proportion)	0.062	0.242	0.069	0.254
Secondary-educated (proportion)	—	—	0.406	0.491
Higher-educated (proportion)	—	—	0.447	0.497
Earnings (before)	41,939	23,727	41,724	23,120
Earnings (after)	53,238	36,916	54,256	39,169
Employment rate (before)	0.979	0.145	0.978	0.148
Employment rate (after)	0.977	0.151	0.974	0.160
Observations	149,475		99,780	

Notes: This table presents summary statistics for parents in two constructed balanced samples (with and without education) whose first child was born between 1993 and 2012. Labor market outcomes are summarized as averages calculated separately around the time of first childbirth. Specifically, pre-childbirth labor market outcomes averaged results from three years to one year prior to the first birth, while post-childbirth outcomes represent averaged results from the year of birth to ten years after.

of the full balanced sample. On average, women have their first child at a younger age than men. Mothers and fathers consist predominantly of natives. Regarding outcomes, women experience declines in both earnings and employment rates following child birth. In contrast, men exhibit relatively stable employment rates and a modest increase in earnings after the birth of the first child.

3 The Evolution of the Child Penalty

3.1 Methodology child penalty

To estimate child-related penalties, we introduce a flexible event study framework that extends the methodology of Kleven et al. (2019b). This adaptable approach is applied across several contexts, accounting for various determinants of childbirth and labor market outcomes. We begin by estimating a baseline model to quantify average child penalties over the full period from 1989 to 2022. We also briefly discuss the heterogeneity by education and migration background. Next, we adopt a cohort-specific approach to analyze how child penalties have evolved across birth cohorts over the past three decades.

A flexible framework In applying the conventional event study methodology (Kleven et al., 2019b) to explore heterogeneity across different groups, researchers often estimate separate regressions for subsamples of the full balanced dataset (Nieto, 2021; Rellstab, 2024; Adams-Prassl et al., 2024). While this approach is straightforward, it becomes inefficient when the number of subgroups is large (e.g., when defined by birth cohort) and poses a risk of overfitting when subgroup sample sizes are small. To address these limitations, we propose a flexible framework that pools all observations into a single regression and includes group-specific dummy variables to control for heterogeneity. This approach accommodates a broad range of specifications and can be simplified to replicate the conventional baseline model.

The following flexible regression estimates the labor market outcome of interest Y^g_{irst}

for individual i in subgroup r of gender g in year s at event time t:

$$\begin{aligned} Y_{irst}^{g} = & \sum_{r \in R} \sum_{t \neq q} \alpha_{rt}^{g} \mathbb{1}\left[eventtime = t\right] \cdot \mathbb{1}\left[group = r\right] + \sum_{r} \eta_{r}^{g} \mathbb{1}\left[group = r\right] + \\ & + \sum_{k} \beta_{k}^{g} \mathbb{1}\left[age = k\right] + \sum_{s} \gamma_{s}^{g} \mathbb{1}\left[year = s\right] + \mu_{irst}^{g}. \end{aligned} \tag{1}$$

Here, q is the baseline event time. We include year and age fixed effects to account for changes in the socio-economic environment and life-cycle trends. Group dummy variables are used to control for heterogeneity across subpopulations, like unobserved differences between natives and immigrants. A key assumption of Equation (1) is that all subgroups experience the same business cycle and life-cycle patterns, which may not hold in certain contexts. As implied by its design, the flexible framework allows for adjustment of covariates to accommodate such deviations when necessary.

The r-specific child penalty by gender is defined as the percentage change in a labor market outcome resulting from the birth of the first child, calculated as follows:

$$P_{rt}^{g} \equiv \frac{\hat{\alpha}_{rt}^{g}}{E\left[\tilde{Y}_{irst}^{g} | t\right]}, \tag{2}$$

where $\tilde{Y}_{irst}^{g} = \hat{Y}_{irst}^{g} - \sum_{r \in R} \sum_{t \neq q} \hat{\alpha}_{rt}^{g} \mathbb{1}\left[eventtime = t\right] \cdot \mathbb{1}\left[group = r\right]$ represents the predicted counterfactual outcome for individuals who are not yet parents. The relative child penalty, which quantifies the child penalty on women relative to men (Kleven et al., 2019b), is then given by:

$$CP_{rt} \equiv \frac{\hat{\alpha}_{rt}^{m} - \hat{\alpha}_{rt}^{w}}{\tilde{Y}_{irst}^{w}}. \tag{3}$$

Given the inherent difficulty in formulating an analytical form for the confidence interval of the child penalty by gender and the relative child penalty, we use a bootstrap approach with 1000 replications to derive their 95% confidence intervals.

Standard model We begin by simplifying the flexible framework to align with the standard event study approach, revisiting the estimation strategy of Rabaté and Rellstab (2022). Extending the data period to 1989—2022, we estimate the average child penalties in the Netherlands over the past three decades. The baseline event time is set at $q = -3$ to account for women's labor market trajectories associated with fertility-related participation, as in Rabaté and Rellstab (2022). Our balanced panel includes parents whose first child was born between 1993 and 2012, with observations ranging from four years before to ten years after childbirth. Since these outcomes are estimated separately for females and males in the panel, group dummies for gender are omitted from the regression specification. The empirical specification can then be simplified to:

$$Y^g_{ist} = \sum_{t \neq -3} \alpha^g_t \mathbb{1}[eventtime = t] + \sum_k \beta^g_k \mathbb{1}[age = k] + \sum_s \gamma^g_s \mathbb{1}[year = s] + \nu^g_{ist}, \quad (4)$$

which matches the expression in Rabaté and Rellstab (2022).

Heterogeneity by education and migration background To examine heterogeneity in the child penalty among parents by education and migration background we can use the following specific version of our flexible specification:

$$\begin{aligned} Y^g_{ibst} = & \sum_b \sum_{t \neq q} \alpha^g_{rt} \mathbb{1}\left[eventtime = t\right] \cdot \mathbb{1}\left[background = b\right] \\ & + \sum_b \sum_k \beta^g_{bk} \mathbb{1}\left[age = k\right] \cdot \mathbb{1}\left[background = b\right] + \sum_s \gamma^g_s \mathbb{1}\left[year = s\right] + \mu^g_{ibst}. \end{aligned} \quad (5)$$

Relative to Specification (1), we introduce flexible interactions between age and background characteristics to account for heterogeneous age–earnings profiles across different groups (Adams-Prassl et al., 2024).[17]

Heterogeneity by birth cohorts To study the evolution of the child penalty over time, we compare differences between women and men who became first-time parents in the

[17] We still assume that business-cycle effects are uniform across subgroups.

same year and examine trends across cohorts. To implement this approach, we introduce a cohort-specific estimation framework with the following specification:

$$\begin{aligned} Y_{ict}^{g} &= \sum_{c}\sum_{t\neq -3}\alpha_{ct}^{g}\mathbb{1}[eventtime = t]\cdot\mathbb{1}[cohort = c] \\ &\quad + \sum_{k}\beta_{k}^{g}\mathbb{1}[age = k] + \sum_{c}\eta_{c}^{g}\mathbb{1}[cohort = c] + \nu_{ict}^{g}. \end{aligned} \tag{6}$$

Due to the linear relationship between event time t, birth cohort c, and calendar year s ($c = s - t$) we include only birth cohort fixed effects.[18] The cohort-specific event time coefficients α_{ct}^{g} thus also capture the temporal dynamics associated with the business cycle.

Next to considering the average child penalty for event time $t \in [0, 10]$, in line with related papers, we also divide the time frame around the first childbirth into five distinct periods: the pre-birth period ($t \in [-2, -1]$), the short term ($t \in [0, 1]$), the medium term ($t \in [2, 4]$), the long term ($t \in [5, 10]$) and the extended-long term ($t \geq 11$).[19] By averaging cohort-specific child penalties within each period, we construct trajectories that illustrate how penalties evolve over time.

3.2 Results child penalty

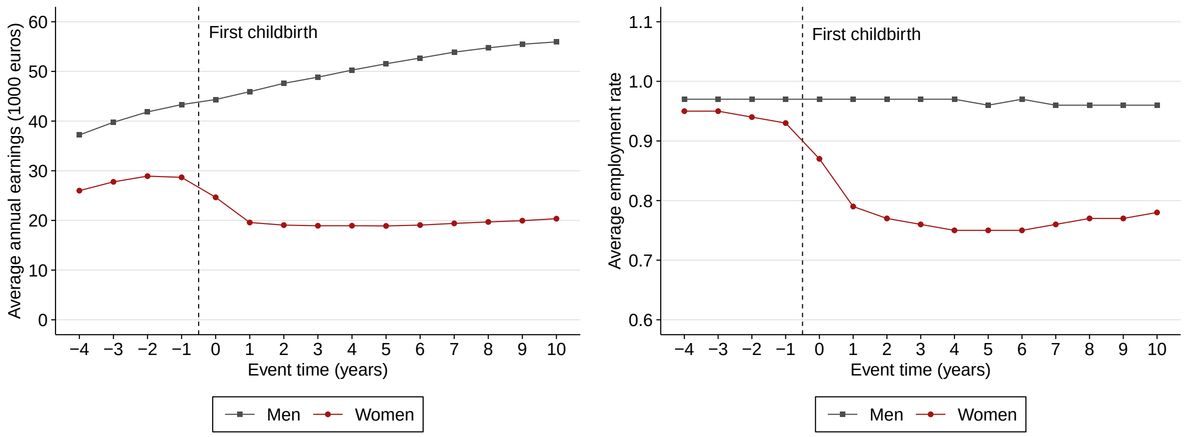
Descriptive evidence Before presenting the estimated impact of children on labor market outcomes under different specifications, we begin with descriptive evidence to assess average trends around the birth of the first child. Figure 2 displays the trajectories of average earnings and employment rates for women and men, measured relative to the year of first childbirth. The descriptive evidence supports the identification assumptions. Prior to childbirth, earnings and employment trends for women and men are approximately parallel, with a marked divergence emerging at the time of the first birth.

[18] In a balanced panel dataset, including year fixed effects would introduce perfect colinearity.

[19] Period definitions vary across the literature. Our categorization is based on observed child penalty patterns in the Netherlands and typical child development milestones. We apply the same classification in Section 4. While the balanced sample includes only $t = 10$ in the extended long-term period, we retain the category for consistency and interpretative completeness.

Figure 2: Average earnings and employment rate relative to the first childbirth

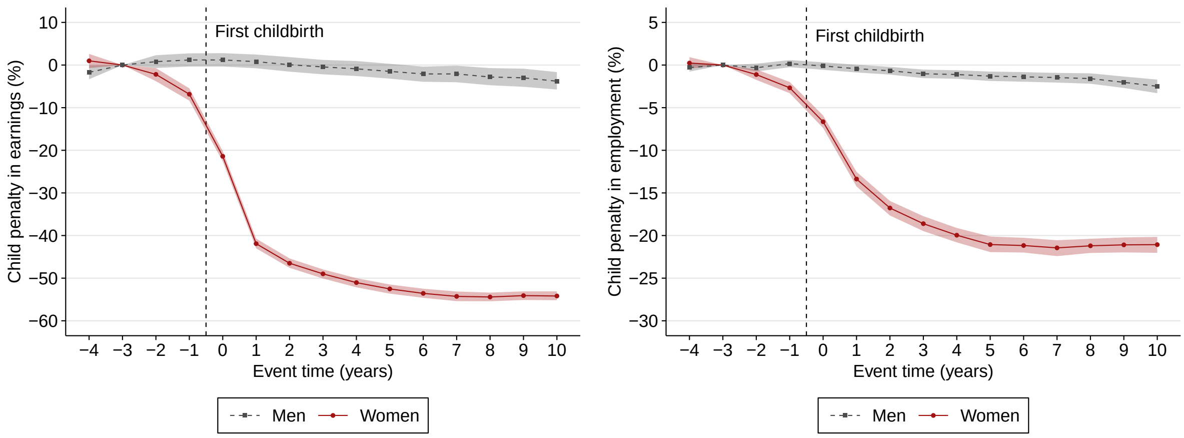
(a) Earnings (b) Employment rate



Notes: The labor market outcomes are calculated as the mean of the data sample for each event time, with observations in 1989-2022.

Figure 3: Average child penalty over the period 1989–2022

(a) Earnings (b) Employment rate



Notes: Parents who have their first child between 1993 and 2012. Panel a and Panel b show the percentage changes of earnings and employment rate for women and men, respectively. The panels also include bootstrapped 95% confidence intervals, represented as ribbons.

Average child penalty by event time Figure 3 presents the average child penalty by event time in the Netherlands over the period 1989–2022. We observe a persistent gender gap in both earnings and the employment rate following the birth of the first child. A sharp divergence between women and men emerges at childbirth, followed by a gradual widening that stabilizes into a long-term plateau. After ten years after childbirth, the relative child penalty in earnings reaches 53%, while the penalty in employment rate becomes 21%. Since child penalties for men are close to zero, the magnitudes of women's child penalties closely approximate the relative child penalties.[20,21] In terms of percentage changes in outcomes for women and men, women experience steep declines in both earnings and employment shortly after childbirth, whereas men's trajectories remain nearly flat.[22] These findings highlight that women in the Netherlands face substantial and persistent labor market penalties following motherhood, while men experience virtually no adverse impact from becoming fathers on their earnings.

We briefly discuss the heterogeneity in the average child penalty by education and migration background, see Figure A.1 and Figure A.2 in the Appendix, respectively. We find substantial disparities across education groups. Higher-educated mothers experience significantly smaller penalties in both earnings and the employment rate than their lower-educated counterparts. In the long run, higher-educated mothers face an earnings penalty of approximately 40%, which is about 20 percentage points lower than that of low-educated mothers.[23] Second, while secondary-educated mothers have only slightly smaller earnings penalties than lower-educated mothers, their employment penalties are considerably lower. Lastly, we observe notable penalties in earnings for low-educated fathers, while higher-educated fathers appear to receive a modest earnings premium following the birth of their first child. Turning to migration background, we find that

[20]Our estimates of child penalties are somewhat higher than those previously reported by Rabaté and Rellstab (2022), but are consistent with expectations based on the evolution of child penalties over time, as revealed by our cohort-specific estimates below.

[21]The employment penalty aligns with findings in Kleven et al. (2024a), which uses Dutch data from 1990 to 2018.

[22]Some downward pre-trends are visible for women beginning during the year of pregnancy. These patterns, also observed by Rabaté and Rellstab (2022), are common in the broader child penalty literature (Andresen and Nix, 2022).

[23]Their employment penalty is around 10%, compared to 20% for secondary-educated mothers and 30% for low-educated mothers.

immigrant mothers (both first- and second-generation) exhibit similar trajectories and face slightly smaller penalties than native mothers. In contrast, employment penalties reveal a clearer distinction: first-generation mothers experience approximately a 5%-point greater drop in employment rates compared to both second-generation and native mothers, whose penalties are of comparable magnitude.[24]

The evolution of the child penalty Figure 4 gives the evolution of the child penalty over birth cohorts. Children have little to no impact on men's earnings and employment rates, regardless of birth cohort. In contrast, women experience significant declines in both earnings and employment rates, for all birth cohorts. However, the average child penalty in earnings falls from approximately 60% for first time mothers in the 1990s to around 35% for first time mothers in the 2010s, while the employment penalty declines from about 25% to 10%. These patterns suggest that first-time mothers in the 1990s faced child penalties that were almost double than those experienced by mothers two decades later.[25]

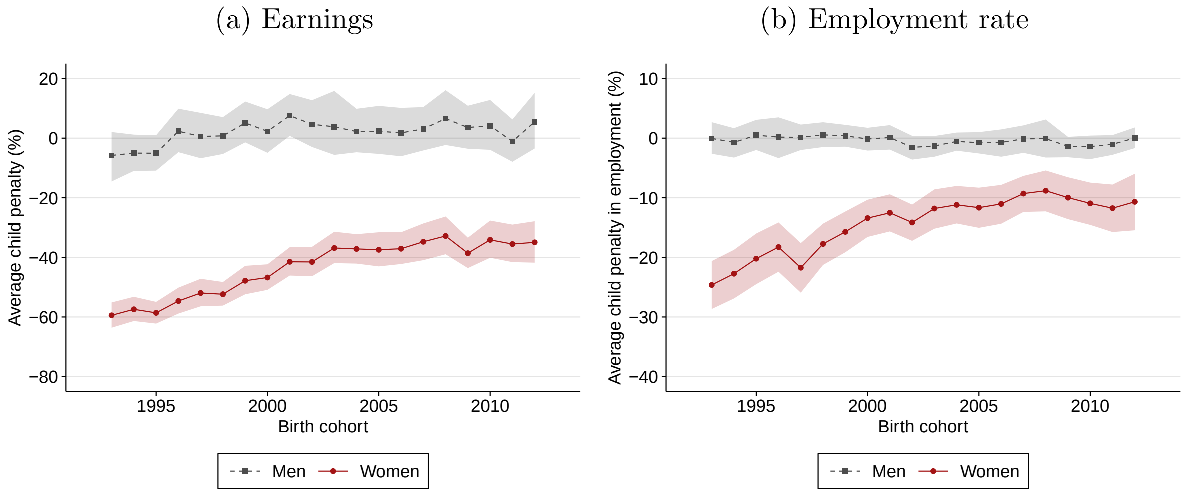
However, also relevant is that the decline in the child penalty occurred mostly during the 1990s and the early 2000s, but appears to have stalled in the mid 2000s. What is perhaps surprising about this result is that there was a substantial policy reform that led to a large increase in child care subsidies from the mid 2000s to the early 2010s, see Figure 5.[26] Indeed, between 2004 and 2009, public expenditures on childcare doubled as a percentage of GDP. However, it is consistent with differences-in-differences studies for the Netherlands that use data around this reform (Bettendorf et al., 2015; Rabaté and Rellstab, 2022), which find no or only modest effects on earnings and the employ-

[24]These differences reflect typical labor market patterns among Dutch native mothers, who are more likely to reduce working hours rather than exit the labor market entirely after childbirth, leading to larger earnings declines but relatively smaller employment penalties. The similarity in employment patterns between native and second-generation mothers suggests a degree of labor market integration among the latter group.

[25]Here we organize the child penalty by the birth cohort of the child. However, we find a similar pattern when we organize the child penalty by the birth cohort of the parents, see Figure A.3 in the Appendix.

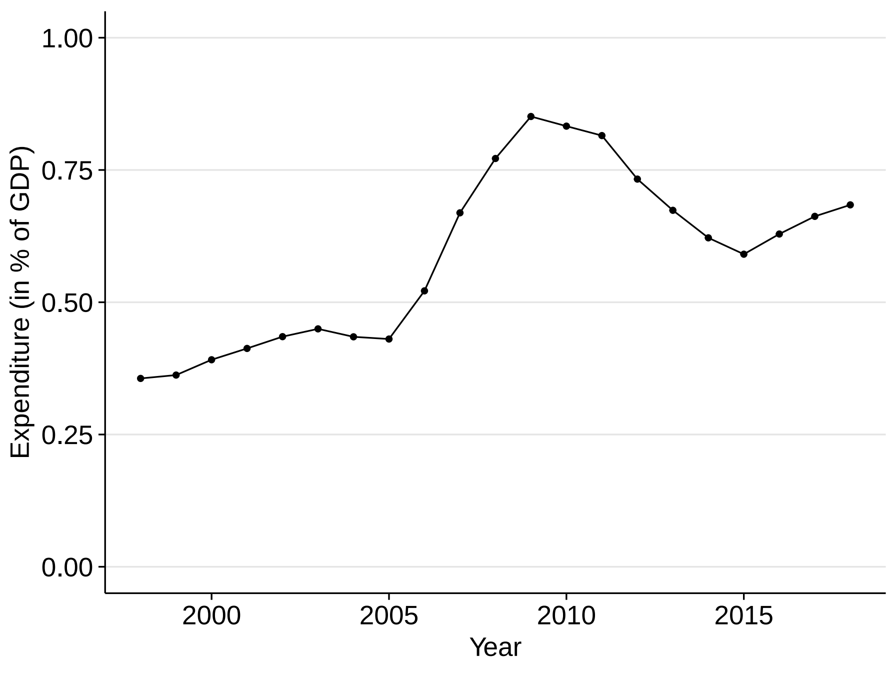
[26]This was also accompanied by a substantial increase in tax credits for working parents, see e.g. Bettendorf et al. (2015).

Figure 4: Child penalty by birth cohorts



Notes: Panel (a) shows the average child penalty for mothers and fathers in earnings by birth cohort of the first child for event time 0 to 10. Panel (b) shows the corresponding child penalty for mothers and fathers in the employment rate. Bootstrapped 95% confidence intervals are also included.

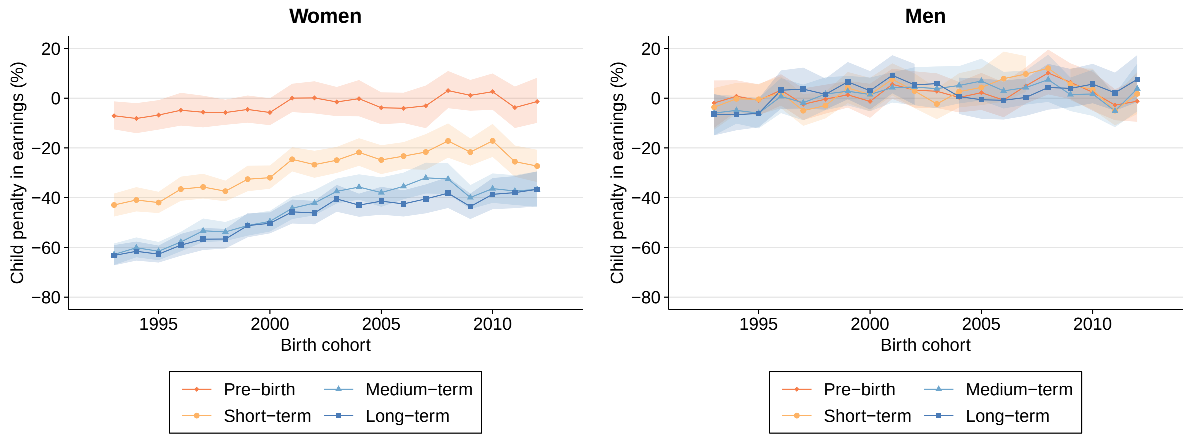
Figure 5: Public spending on childcare and early education (% of GDP)



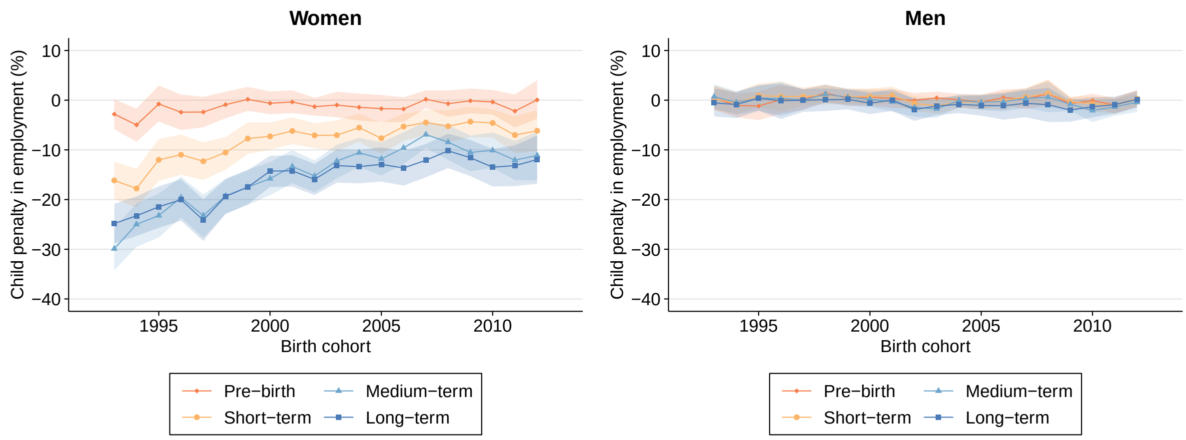
Notes: Public spending on childcare and early education as a percentage of GDP over time. Source: OECD Family Database.

Figure 6: Evolution child penalty by event times

(a) Earnings



(b) Employment rate



Notes: Cohort trajectories of child penalty by gender in earnings (Panel a) and employment rate (Panel b). The trajectories, averaged across parents grouped by the year of their first childbirth, are shown in four stages: (i) pre-birth, (ii) short-term, (iii) medium-term, and (iv) long-term. Bootstrapped 95% confidence intervals are also included.

ment rate.[27] Furthermore, notice that there was a substantial cut in public spending on childcare between 2011 and 2015, following a large cut in the subsidy.

Figure 6 considers the evolution of the child penalty at four distinct stages relative to childbirth (the pre-birth period ($t \in [-2, -1]$), the short term ($t \in [0, 1]$), the medium term ($t \in [2, 4]$) and the long term ($t \in [5, 10]$)). We see that pre-birth penalties are near zero across all cohorts, supporting the validity of the identification strategy. Post-birth penalties show a gradual decline over time, plateauing for cohorts from the mid 2000s

[27]Furthermore, it is consistent with the small and insignificant effects found by Kleven et al. (2024b) for the expansion of subsidized childcare in Austria.

onward. Furthermore, medium- and long-term penalties appear similar in magnitude, indicating the persistence of child-related effects on women's labor market outcomes. However, the gap between short-term and long-term penalties is narrowing, in particular for employment rates.

4 Decomposing Gender-Based Inequality over Time

Next, we consider the evolution of gender-based inequality in earnings and employment, and the role played by the evolution of the child penalty in this.

4.1 Methodology decomposition

Dynamic decomposition Following Kleven et al. (2019b) we decompose gender-based inequality into two components: child-related inequality and residual inequality. Within the residual component, we also examine the roles of education and migration background. To provide deeper insight into the dynamics of child penalties, we extend the decomposition framework by accounting for the evolution of the child penalty over time. Following the event time clustering introduced in Section 3, we divide the years after first childbirth into four stages (short term, medium term, long term, and extended long term (event time 11 and more)) and estimate the contribution of child-related penalties at each stage.

Following the basic dynamic decomposition approach in Kleven et al. (2019b), we extend the cohort-specific specification by gender (6) as follows:

$$Y_{ict}^{g} = \sum_{c} \sum_{t \neq -3} \alpha_{ct}^{g} \mathbb{1}\left[eventtime = t\right] \cdot \mathbb{1}\left[cohort = c\right] + \sum_{k} \beta_{k}^{g} X_{kic}^{g} + \nu_{ict}^{g}, \tag{7}$$

where the covariates Xs include a full set of age dummies and calendar year dummies. [28] When accounting for the effects of education and migration background, the covariates also include controls based on generation and three levels of education.[29]

[28]This specification aligns with the implementation used by Kleven et al. (2019b) in their published code.

[29]As the background controls are dummies, an identification problem arises in the this detailed de-

We define the average aggregated gender inequality in year s as:

$$\Delta_{s|\mathcal{T}} = \frac{E\left[\hat{Y}^m_{ict}|s,\mathcal{T}\right] - E\left[\hat{Y}^w_{ict}|s,\mathcal{T}\right]}{E\left[\hat{Y}^m_{ict}|s,\mathcal{T}\right]},$$

where $\mathcal{T} = \{t|t \geq 0\}$ represents the post-birth period, and $\hat{Y}^g_{ict}$ is the estimated labor market outcome by gender in year $s = c + t$. Compared to the literature (for example, Kleven et al. (2019b) and Glogowsky et al. (2025)), we consider the gender inequality decomposition among already-parents, by selecting observations with event time $t \geq 0$. Applying the standard Oaxaca-Blinder decomposition approach and rearranging terms, we can formulate $\Delta_{s|\mathcal{T}}$ as:

$$\Delta_{s|\mathcal{T}} = \underbrace{\frac{E\left[P_{ct}\tilde{Y}^w_{ict}|s,\mathcal{T}\right]}{E\left[\hat{Y}^m_{ict}|s,\mathcal{T}\right]}}_{\text{child-related gap}} + \underbrace{\frac{\sum_k \left(\hat{\beta}^m_k - \hat{\beta}^w_k\right) E\left[X^m_{kic}|s,\mathcal{T}\right]}{E\left[\hat{Y}^m_{ict}|s,\mathcal{T}\right]}}_{\text{coefficient effects}} + \underbrace{\frac{\sum_k \hat{\beta}^w_k \left\{E\left[X^m_{kic}|s,\mathcal{T}\right] - E\left[X^w_{kic}|s,\mathcal{T}\right]\right\}}{E\left[\hat{Y}^m_{ict}|s,\mathcal{T}\right]}}_{\text{characteristic effects}}, \tag{8}$$

where P_{ct} is the cohort-specific relative child penalty defined in Section 3[30], $\tilde{Y}^w_{ict}$ and $\hat{Y}^m_{ict}$ are the predicted counterfactual outcomes for women and men. The first term on the right side of Equation (8) captures the child-related inequality within the aggregated gender gap. The second term and the third term present the coefficient effects and characteristic effects of covariates respectively. Note that the child-related inequality, so defined, may not capture the full impacts of children, part of which may be included in the residual (Cortés and Pan, 2023).

We now focus on the child-related term in Equation (8). For each calendar year, the child-related gap is an aggregate of relative child penalties across various event times and

composition (Ramini and Nazari, 2021). We then apply the normalization of Yun (2005) and consider the average effect using different education or migration groups as reference.

[30]Although women's labor market performance is slightly behind of men, which can related to birth participation, we only focus on the child penalties since the birth of the first child, that is, with event time $t \geq 0$.

birth cohorts. Therefore, we refine the child-related term into the following expression:

$$\frac{E\left[P_{ct}\tilde{Y}_{ict}^{w}|s,t\geq 0\right]}{E\left[\hat{Y}_{ict}^{m}|s\right]}=\sum_{T\in\{T_1,T_2,T_3,T_4\}}\underbrace{P\left[t\in T\right]\cdot\frac{E\left[P_{ct}\tilde{Y}_{ict}^{w}|s,t\in T\right]}{E\left[\hat{Y}_{ict}^{m}|s\right]}}_{\text{period-specific child-related inequality}}. \tag{9}$$

Here $0 \leq T_1 \leq 1$, $2 \leq T_2 \leq 4$, $5 \leq T_3 \leq 10$, and $T_4 \geq 11$, represent the short-term, medium-term, long-term, and extended-long-term periods respectively. The term $P\left[t \in T\right]$, named as period probability, denotes the probability that the event time t falls within a specified period. This extension builds on the partition theorem in probability (Grimmett and Welsh, 2014), offering a detailed breakdown of child-related inequality based on the trajectory of relative child penalties.

This decomposition approach is sensitive to the distribution of period probabilities. In sufficiently large datasets, event time t tends to be uniformly distributed across calendar years, which makes the weight assigned to each period roughly proportional to its length. As a result, extended long-term child penalties carry the greatest weight, meaning that estimates of child-related inequality are disproportionately influenced by parents who had their first child decades earlier. This highlights the presence of the sample selection in decomposition-based analyses. Moreover, identifying long-run child penalties (e.g., at $t = 20$) is methodologically challenging and potentially unreliable (Borusyak et al., 2024). In light of this, we restrict our analysis of child-related inequality to the long-term period, focusing on parents whose first child is aged 0 to 10. However, we will also consider the results when we do not restrict the event time window, to show how much of a difference this makes.

Empirical strategy for extrapolation We analyze gender inequality over the past three decades (1989–2022). Following the data construction from Kleven et al. (2019b), we utilize a complete dataset of observations for parents whose first child was born between 1979 and 2021. The sample is restricted to parents aged 20 to 45 at the time of their first child's birth and with a known migration background. This design allows us to observe parents who had their first child in 1979 up to event time $t = 43$.

For birth cohorts prior to 1992, we only have data for event time $t \geq -2$. Consequently, cohort-specific relative child penalties cannot be directly estimated for these earlier cohorts. To address this limitation, we employ a linear extrapolation method, following the approach of Kleven et al. (2019b), to estimate relative child penalties across all birth cohorts and event times, ensuring the observed data includes the baseline $t = -3$. Aligned with the detailed division of child-related inequality, we also extrapolate child penalties separately, resulting in five distinct trends, see Figure A.5 and Figure A.6 in the Appendix. Through these linear extrapolations, we establish cohort-specific child penalties, P_{ct}, for every event time $t \geq -3$ within the calendar years 1989–2022. These extrapolations enable the decomposition of aggregated gender inequality into child-related inequality and residual inequality over the past three decades.

4.2 Results decomposition

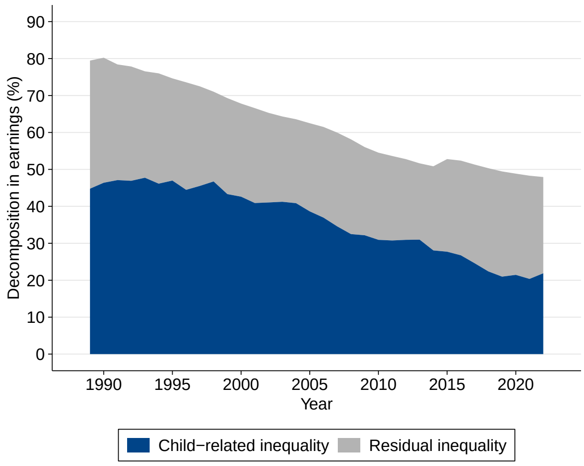
Figure 7 presents the decomposition of gender inequality in labor market outcomes from 1989 to 2022. Panel 7a and Panel 7b show the share of the total gender gap attributable to child-related inequality, limited to the ten years following the birth of the first child. Panels 7c and 7d extend the analysis by incorporating gender-inequality related to education and migration background.[31]

The decomposition of gender inequality over time reveals distinct patterns for earnings and employment outcomes. In earnings, the total gender gap declined steadily from around 80% in the early 1990s to below 50% in the early 2020s, while the child-related component fell from around 45% to around 20% over the same period. These parallel downward trends suggest that, although child-related inequality accounts for a substantial share of the gap, a persistent residual component remains, also after three decades. For the employment rate, the total gender gap declined more sharply, from close to 30% in the early 1990s to below 10% in the early 2020s, with most of the decline happening before 2010. Child-related inequality in employment also decreased, from around 25%

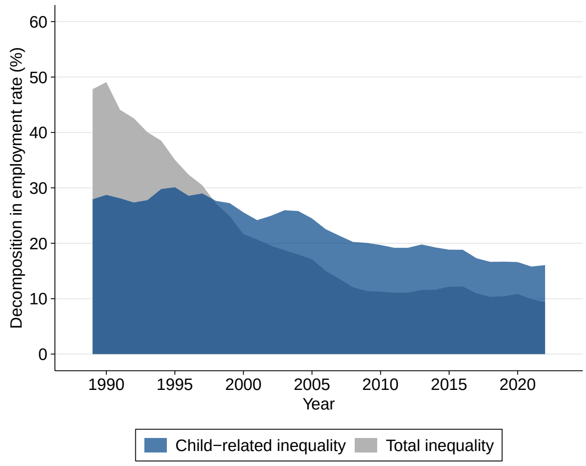
[31]Figure A.4 shows the evolution of the explanatory variables in the decomposition regression and Table A.2 gives the regression results.

Figure 7: Decomposition of gender inequality

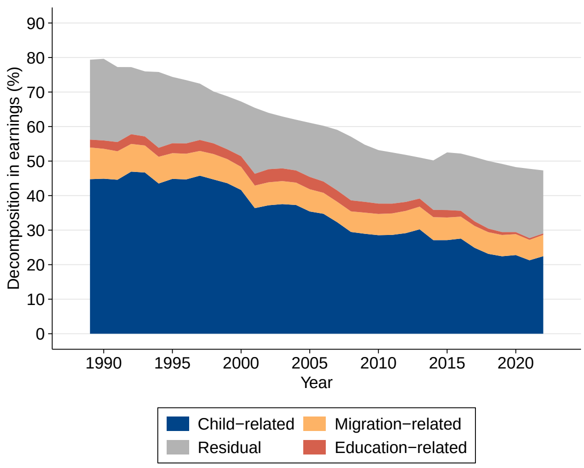
(a) Child-related and residual inequality in earnings



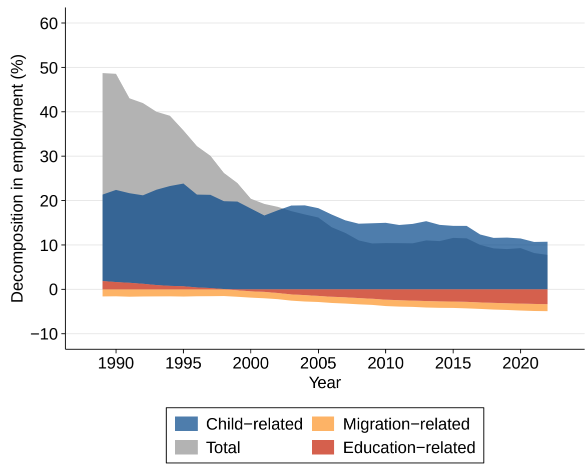
(b) Child-related and residual inequality in the employment rate



(c) Including education and migration background: earnings



(d) Including education and migration background: employment rate



Notes: We limit the impact of children to the ten years after the first childbirth (event time 0 to 10). Note that the migration-related and education-related gender gaps includes both the effect of different backgrounds (explained effect) and the effect of different coefficients (unexplained effect).

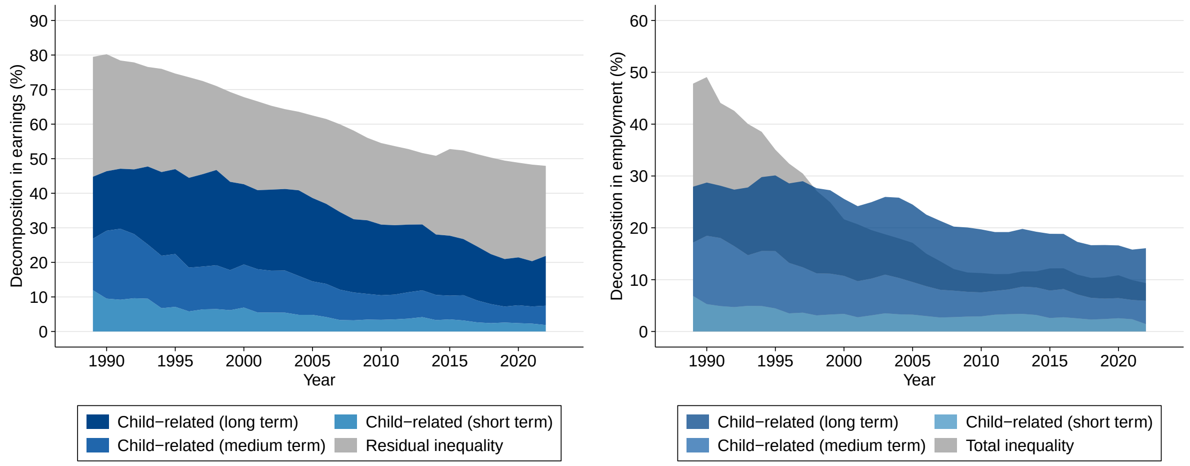
to around 15%. Furthermore, the analysis reveals a negative residual component in employment inequality, suggesting that, absent child-related factors, women would have higher employment rates than men. This finding aligns with Kleven et al. (2024a).

Migration-related differences also contribute to the gender gap, both in earnings and in employment. The contribution is approximately 8% of the earnings gap and even slightly negative for employment. Educational attainment accounts for little of the earnings

Figure 8: Decomposition gender-based inequality for different stages

(a) Child-related and residual inequality in earnings

(b) Child-related and residual inequality in the employment rate

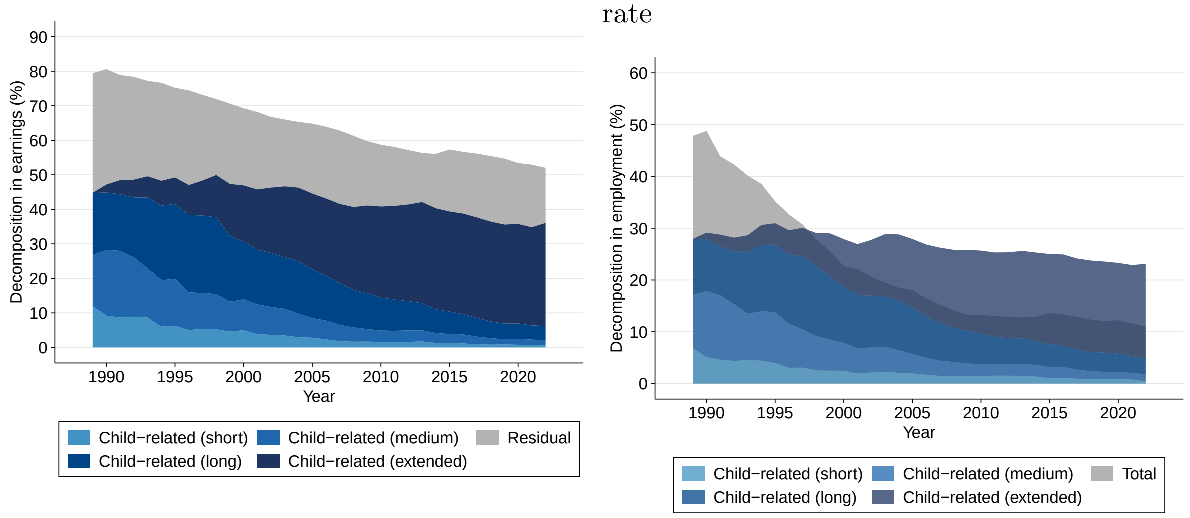


Notes: The decomposition shows the contribution to gender-related inequality of children in the short-term, medium-term, and long-term. The event time is 0 to 10.

Figure 9: Decomposition without restricting event time

(a) Detailed decomposition of earnings

(b) Detailed decomposition of the employment rate



Notes: The decomposition shows the contribution to gender-related inequality of children in the short-term, medium-term, long-term and extended long-term (>10 after the birth of the first child). The event time is unrestricted.

gap, and by the 2020s contributes virtually nothing. Its impact on employment turns negative after 1998. These negative components indicate that differences in education and migration background tend to reduce, rather than reinforce, the gender gap in the employment rate.

Figure 8 further disaggregates child-related inequality by distinguishing short-term, medium-term, and long-term penalties following the birth of the first child. These results reveal that medium- and long-term child responsibilities play an important role in child-related inequality.

In the preceding analysis we focus on the first ten years after child birth, because we are concerned about composition effects if we do not restrict the event time window. To illustrate this point, we replicate the decomposition without an event time restriction, following the sample selection criteria in Kleven et al. (2019b). Figure 9 gives the results. In this case we find that child-related inequality has remained relatively stable over the past three decades, declining modestly from approximately 48% to 38% in earnings, and from 28% to 25% in the employment rate. These findings are more in line the findings in Kleven et al. (2019b), in the sense that gender-based inequality related to children remains relatively flat, though, in contrast to Kleven et al. (2019b) a substantial residual gap still remains. However, this is driven by the contribution of the event time after the first 10 years after the birth of the first child, as the share of parents with this 'extended long' event time increases mechanically when we move from 1989 to 2022, see also Figure A.7 in the Appendix. Hence, at least in our case, but presumably in other studies as well, the sample used in the decomposition of gender-based inequality matters a lot for the contribution of child-related inequality to the gender gap. We prefer to keep the event-time window fixed, so that we are comparing the same group of parents over time.

5 Conclusion

This paper examines the evolution of child-driven gender inequality in the Dutch labor market over the past three decades, using high-quality administrative panel data. We assessed the impact of childbearing through two main approaches: (1) estimating child penalties with a focus on temporal heterogeneity using an event study design, and (2) decomposing child-related inequality within the overall gender gap to analyze its evolution over time. Our methodology builds on the foundational framework introduced by Kleven et al. (2019b), particularly the event study and dynamic decomposition approaches. Using our flexible event study approach, we document a substantial decline in the child penalty in earnings for mothers over time from 60% in the 1990s to 35% for mothers in the 2010s. As for the contribution of child-related inequality to gender-based inequality, we show that in earnings, total and child-related inequality have declined in parallel, leaving a persistent residual gap. For employment, a negative residual component has emerged since the late 1990s, suggesting that, absent child-related effects, women tend to outperform men in employment participation. We also show that the sample selection for the decomposition matters a lot for the contribution of child-related inequality to total gender inequality. Using a sample selection that implicitly includes more and more parents with longer and longer event times may obscure the decline in child penalties over time.

As already indicated in the Introduction, our findings for the Netherlands differ quite a lot from the handful of studies documenting the evolution of the child penalty and the contribution of child-related inequality to gender-based inequality. The decline in the child penalty for mothers is much larger than in Austria, Denmark, Sweden and the US, whereas the child penalty in Germany even increases. We also find a stronger decline in gender-related inequality than in the other countries, starting from a higher level. However, in contrast to the other countries, we also find a substantial decline in child-related inequality, though part of this is due to the sample selection, which as we have shown is not innocuous. Explaining these cross-country differences in the evolution of the child penalty in earnings and the contribution to gender-based inequality is crucial for a better understanding of the role played by children and other factors in the evolution of gender-based inequality.

Declarations

Funding: No funding has been received for the research in this paper.

Conflicts of interest/competing interests: The authors declare that they have no conflict of interest.

Availability of data and material: The datasets are available via remote access at Statistics Netherlands.

Code availability: All codes used in the analysis are available on request.

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Supplementary Material to:

"The Evolution of the Child Penalty and Gender-Related Inequality in the Netherlands, 1989-2022"

Renren Gan   Egbert Jongen   Simon Rabaté   Bo Terpstra

September 2025

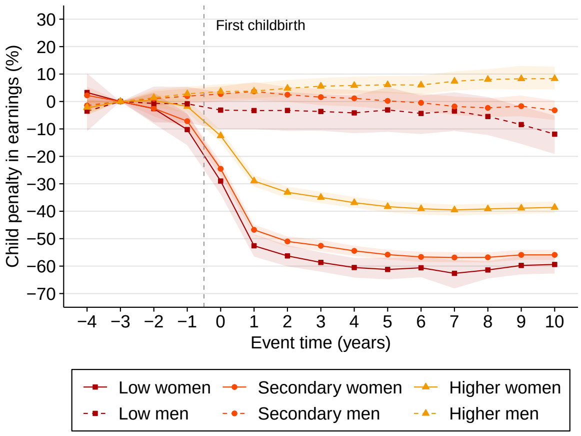
Table A.1: Studies evolution child penalty and contribution to gender-based inequality in earnings

Study	Country	Child penalty mothers			Source	Gender- and child-related inequality						Source
		Event time	Start year	End year		Event time	Age	Start year		End year		
								Gender-related	Child-related	Gender-related	Child-related	
This paper	NLD		1993	2012				1990		2022		
		0–10	59	35	Fig. 1	0 to 10	20 – 55	80	46	48	22	Fig. 1
Kleven et al. (2019b)	DNK		1990	2003				1990		2013		
		0–10	27	23	Fig. 4	-5 to 43	18 – 64	35	19	23	18	Fig. 5
Kleven et al. (2024b)	AUT		1990	2008				1990		2017		
		0–10	65	61	Fig. D.VII	-5 to $>$ 30	15 – 64	51	38	42	32	Fig. 12
Glogowsky et al. (2025)	GER		1980	2000				1990		2013		
		0–10	56	62	Fig. 2	-3 to $>$ 10	25 – 45	67	12	52	32	Fig. 12
Sundberg (2024)	SWE		1991–95	2011–15								
		0–10	40	35	Fig. 4							
Cortés and Pan (2023)	US							1990s		2010s		
						-5 to 10	20 – 55	53	29	45	30	Fig. 2
Kleven (2022)	US		1990–94	2010–14								
		0–10	42	30	Fig. 4							

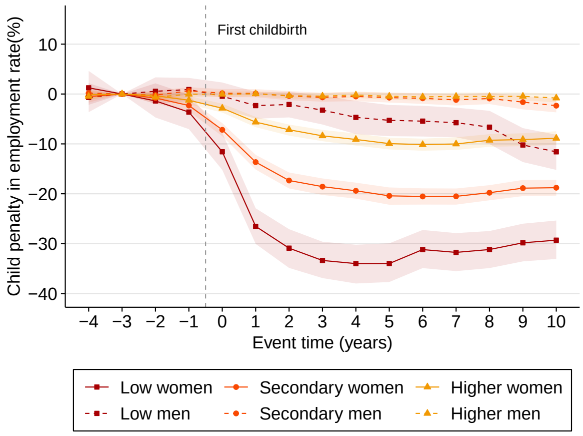
NOTES: This table gives an overview of the handful of papers that also consider the evolution of the child penalty over time and/or the contribution of child-related inequality to total gender inequality (typically for (future) parents, though Glogowsky et al. (2025) also consider non parents.

Figure A.1: Effects of children on women and men by educational attainment

(a) Earnings



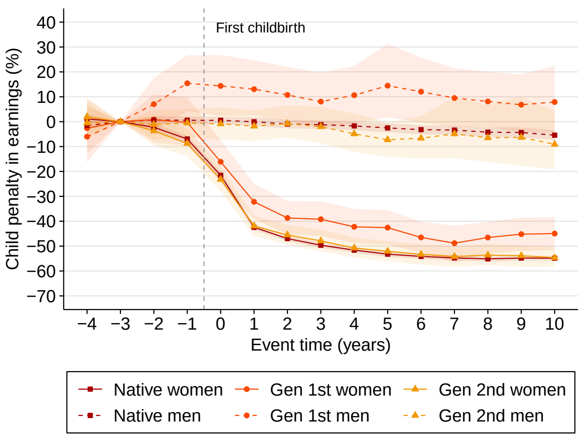
(b) Employment rate



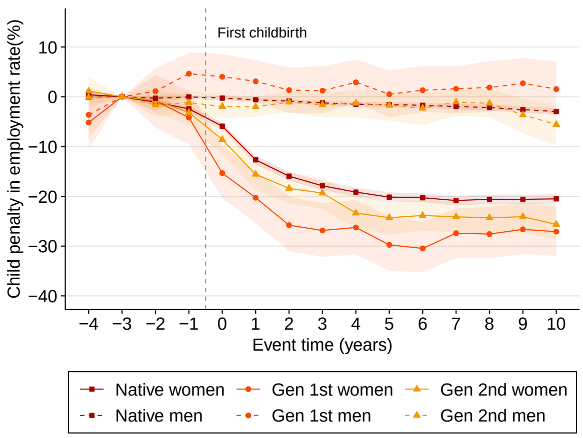
Notes: Bootstrapped 95% confidence intervals are included as ribbons.

Figure A.2: Effects of children on women and men by migration background

(a) Earnings



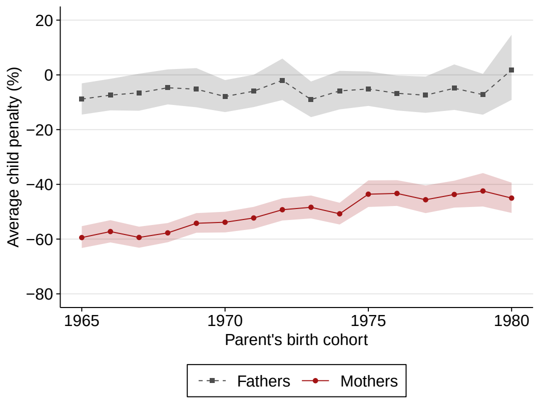
(b) Employment rate



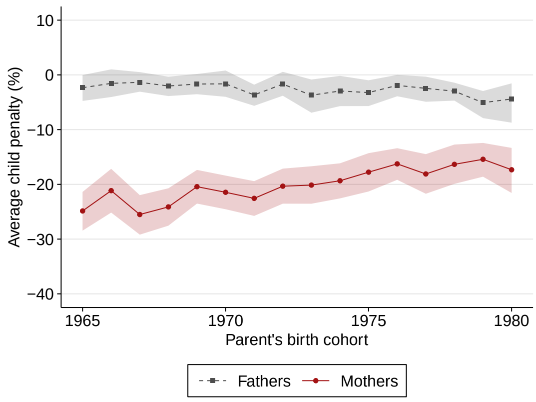
Notes: Bootstrapped 95% confidence intervals are included as ribbons.

Figure A.3: Average child penalty by birth cohort of the parents

(a) Earnings

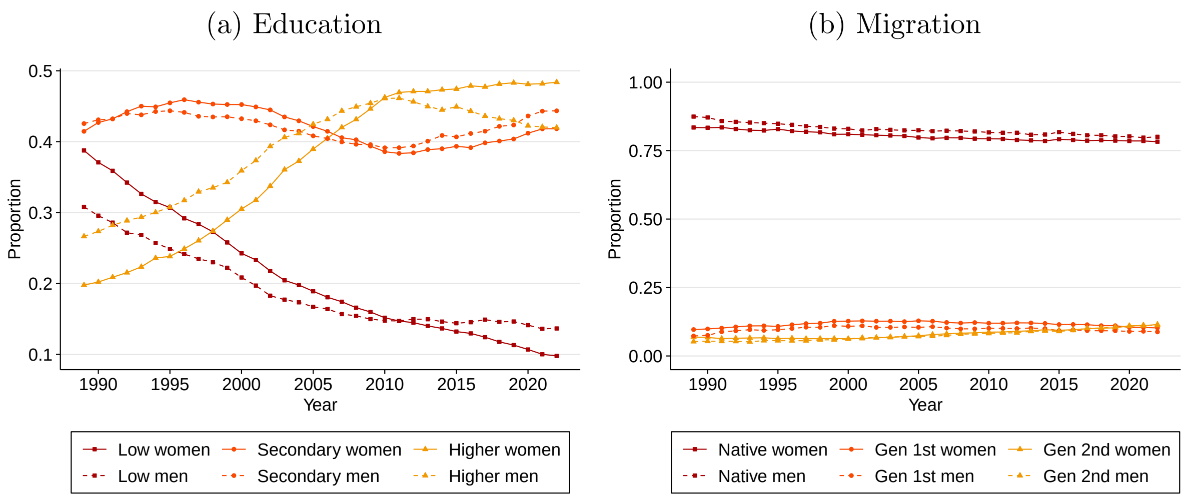


(b) Employment rate



Notes: Average child penalty for event time 0 to 10 by birth cohort of the parents. Bootstrapped 95% confidence intervals are included as ribbons.

Figure A.4: Evolution of variables entering the decomposition



Notes: The figure shows the evolution of the explanatory variables entering the dynamic decomposition, and also for the base group.

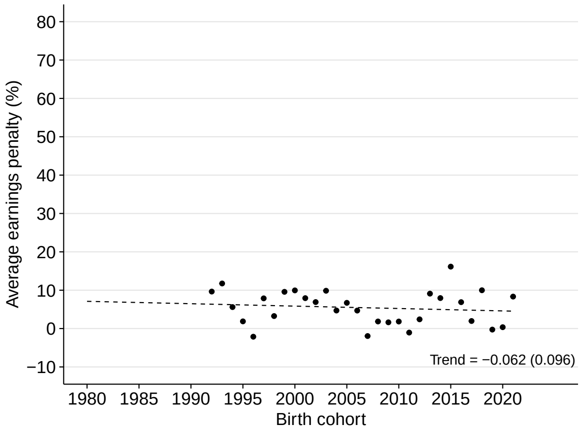
Table A.2: Regression estimates decomposition

	Earnings		Employment	
	Mothers	Fathers	Mothers	Fathers
Secondary-educated	5906.019***	8931.913***	0.164***	0.068***
	(62.374)	(123.867)	(0.002)	(0.001)
Higher-educated	19425.606***	30672.218***	0.222***	0.083***
	(83.663)	(164.300)	(0.002)	(0.001)
First generation	-4573.076***	-14632.511***	-0.161***	-0.096***
	(104.757)	(185.373)	(0.002)	(0.002)
Second generation	-547.618***	-4123.610***	-0.039***	-0.030***
	(113.244)	(243.024)	(0.002)	(0.002)

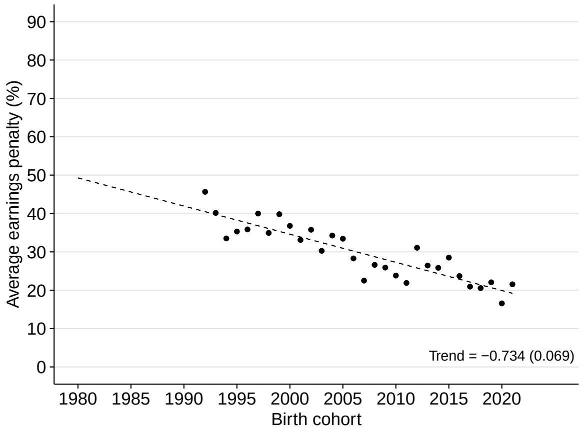
Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.5: The different periods of earnings penalties

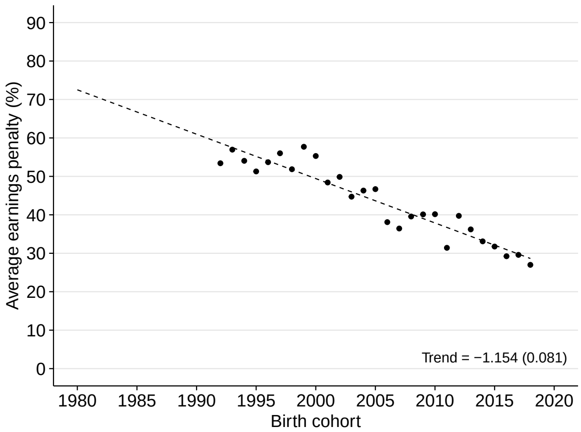
(a) Pre-birth



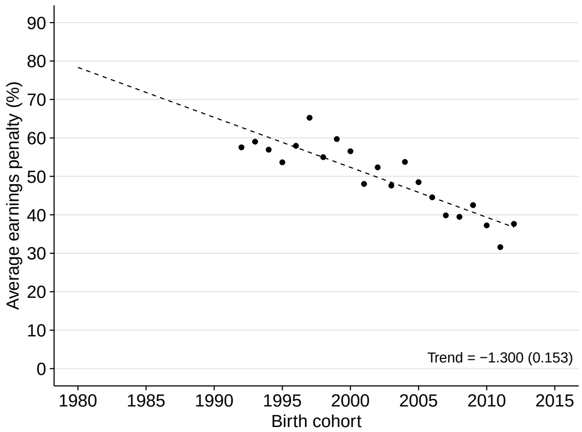
(b) Short-term



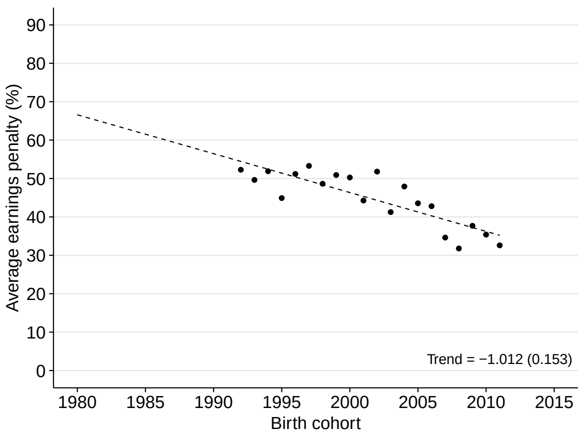
(c) Medium-term



(d) Long-term



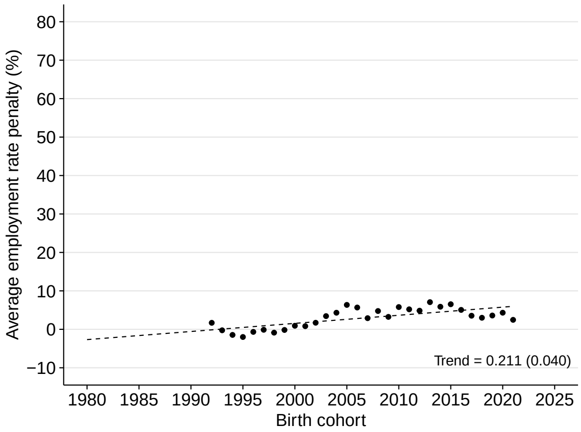
(e) Extended-long-term



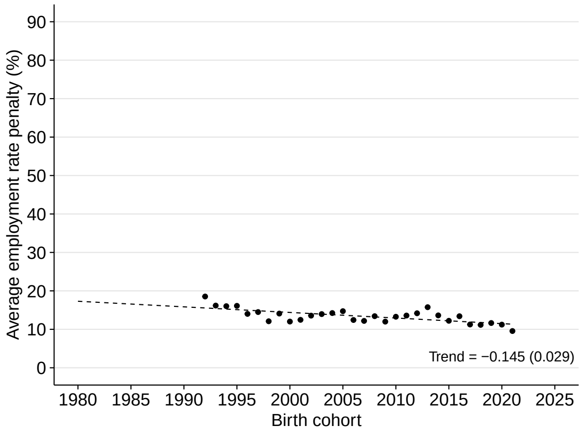
Notes: The different periods of earnings penalties, averaged by birth cohort. Each panel also includes a linear OLS fit.

Figure A.6: The different periods of employment penalties

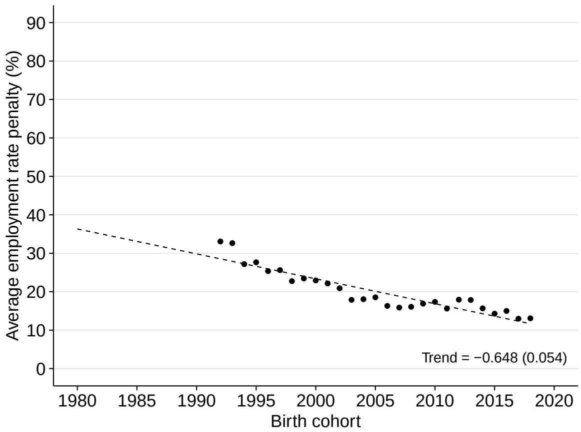
(a) Pre-birth



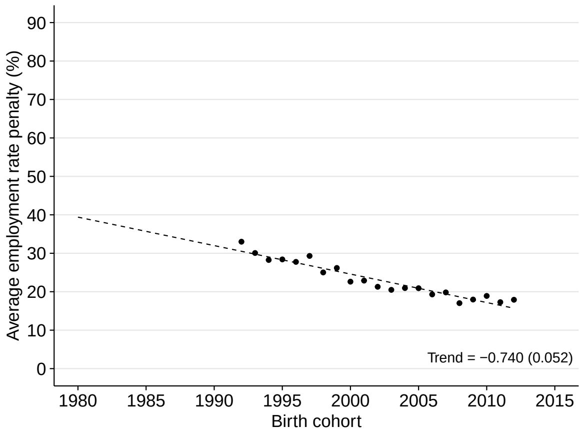
(b) Short-term



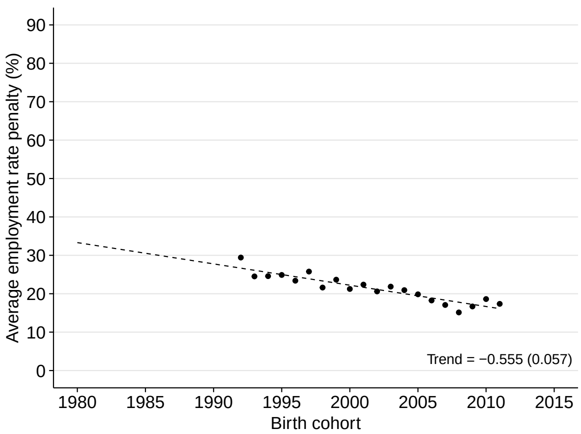
(c) Medium-term



(d) Long-term



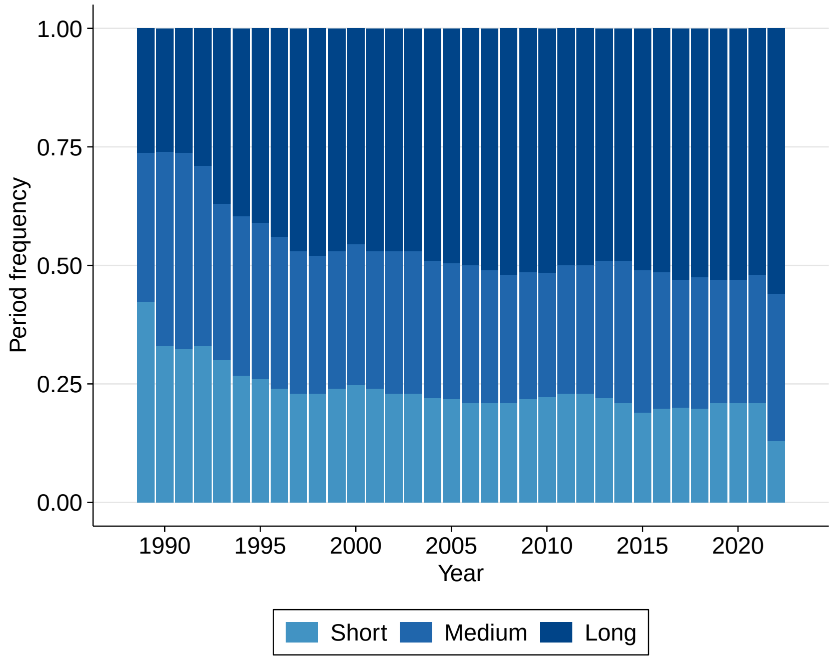
(e) Extended-long-term



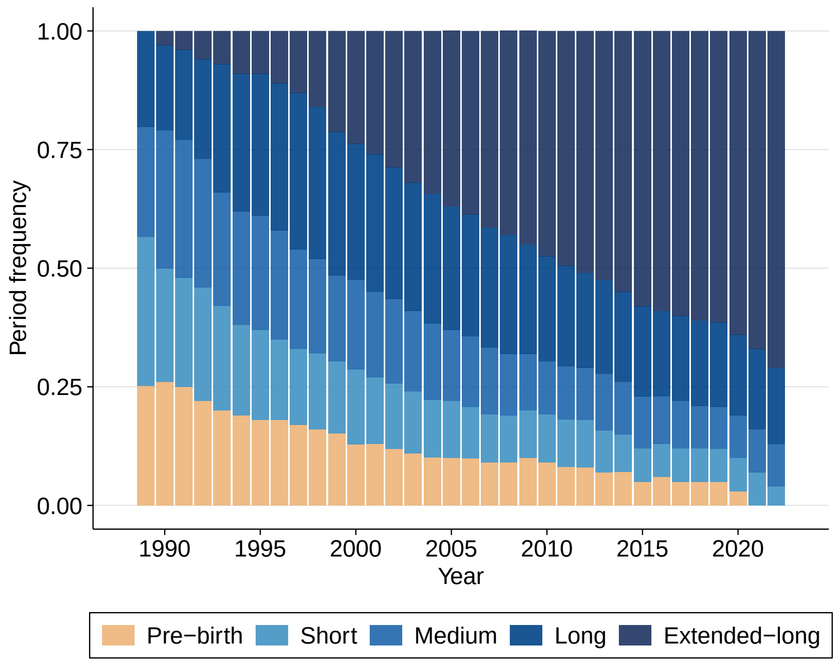
Notes: The different periods of the employment rate penalties, averaged by birth cohort. Each panel also includes a linear OLS fit.

Figure A.7: The fraction of child penalty periods in the decomposition data

(a) Three-stage weight composition



(b) Five-stage weight composition



Notes: Panel b shows the composition of five stages surrounding the first childbirth, while Panel a shows the fractions limited to the first ten years after the first childbirth.