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ABSTRACT

This paper estimates child penalties in labour-market-relevant cognitive skills, such as numeracy but also literacy and problem-solving competencies. We use international PIAAC data and adapt a pseudo-panel approach to a single cross-section covering 29 countries. Numeracy scores, which are associated with the largest returns to skills and pronounced gender differences, decline by 0.11 standard deviations for fathers and an additional 0.07 for mothers. We find no evidence of a deterioration in the occupational skill match for either mothers or fathers. Our findings suggest that changes in general labour market skills such as numeracy competencies explain at most 10% of child penalties in earnings. We additionally show that cross-sectional estimates of child penalties can be sensitive to controlling for predetermined characteristics that vary across cohorts, in our case education.

1. Introduction

Parenthood is associated with large and persistent changes in the labour market outcomes of mothers. After the birth of their first child, employment rates and earnings of mothers fall and typically fail to fully recover, while the labour market outcomes of fathers are much more modestly affected, if at all. This phenomenon is often termed the 'child penalty'.[1] The child penalty has in recent years received a lot of attention in the literature, and has emerged as the most important explanation for remaining gender

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[1] While 'parenthood effects' may be a more precise and neutral expression, throughout the paper, we use the term 'child penalties' as it is the most common term in the literature for the gendered effect of parenthood.

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gaps in labour market outcomes in high-income countries (Cortés and Pan, 2023; Kleven et al., 2019a,b; Kleven, 2025; Kleven et al., 2024a). Biological reasons do not explain long-term penalties (Andresen and Nix, 2022; Kleven et al., 2021), and gender norms are commonly put forward as the main factor determining worse labour market outcomes of mothers, especially in the short-run.

However, we still know little about whether the initial labour market shocks for mothers are accompanied by a drop in labour market skills, e.g. because of reduced skill use during the employment interruption, or a lack of skill accumulation due to reduced on-the-job skill growth and foregone training opportunities. Such skill loss could reinforce short-term employment interruptions, and therefore have long-term consequences for mothers' labour market trajectories. Hence, understanding the dynamics of skills might be important for understanding child penalties in employment and wages, and for judging the effectiveness of potential skill-preserving policies.

In this paper, we document how a set of general labour market skills evolves around parenthood. The skills we focus on are not tied to specific firms or occupations, and have well-documented and sizeable labour market returns. We primarily analyse numeracy skills, where gender differences are large[2] and which have been shown to be important predictors of labour market outcomes. On average, a one standard deviation higher level of numeracy skills is associated with an 18 percent wage premium among prime-age, full-time workers (Hanushek et al., 2015). We follow the approach of Kleven (2025) and Kleven et al. (2024a), who develop a matching procedure in repeated cross-sectional data to estimate child penalties in labour market outcomes such as employment and wages. While it is not possible to observe the same individuals before and after the birth of their first child in data lacking a panel structure, they show that child penalties obtained using their matching procedure closely mimic those estimated with panel data. We adapt their procedure to a cross-country setup, and apply it to a single cross-section from the Programme for the International Assessment of Adult Competencies (PIAAC), which includes indices for labour market skills in different domains for individuals aged 16 to 65. While it does not allow us to follow the same individuals over time, the PIAAC dataset is ideally suited for our study due to its detailed assessment of adult skills, the rich set of background variables, and its representativeness and consistency across a large set of countries.

Once we control for pre-determined characteristics, and in particular education, we find that numeracy skills of fathers decline by 11 percent of a standard deviation in early parenthood. Long-run estimates (10 years after childbirth) for mothers are 6 percent of a standard deviation more negative (statistically significant at the 10% level) than those of fathers. This corresponds to less than one eighth of the difference in average numeracy skills between those with upper or post-secondary education and those with tertiary education.[3] Using returns to labour market skills as measured in PIAAC (Hanushek et al., 2015), which we confirm using our estimation sample, these lower post-childbirth numeracy skills would translate into approximately 1% lower wages for mothers compared to fathers. We can rule out effect sizes larger than 2.5% and hence conclude that child penalties in numeracy can at most explain 10% of the long-term child penalty in monthly earnings (24%) that we estimate in our international sample. Child penalties in literacy and problem-solving skills exhibit comparable patterns, with somewhat larger drops for both mothers and fathers, but no statistically significant differences in short- or long-term patterns between mothers and fathers.

We also provide evidence on whether parenthood is associated with a worse match between own skills and occupational skill requirements. Although we observe no pronounced differential skill evolution around childbirth for mothers and fathers, parents might still select into jobs with different skill requirements after the birth of their first child, e.g. in favour of more job flexibility or security.[4] This selection could be associated with mothers' jobs offering lower returns to existing skills which could preserve or exacerbate the gender pay gap, even in the absence of differential skill development after childbirth for mothers and fathers. Additionally, different occupational selection after childbirth for mothers might also lead to a decrease in job-related skills in the longer run, i.e. beyond our observation period, because of reduced usage patterns.[5] We find that parenthood in our sample is not associated with worse occupational skill matches for mothers using the method from Bandiera et al. (2024) (see also Perry et al., 2014, for a related approach), that connects occupation-specific skill demand to the skill levels of workers in these occupations as a measure of skill mismatch.

Furthermore, we look at outcomes related to numeracy skills, such as the intensity of their use and specific components of the numeracy assessment. We document a substantial decrease in the likelihood that women report using numeracy skills *at work* after childbirth (which is entirely explained by their employment interruptions), but mothers' reduced skill use does not translate into lower skills. For men, the decrease in skill use is much smaller, and for neither parent is there an equivalent decrease of the use of numeracy skills *in everyday life*. To analyse different numeracy components, we rely on raw item-level responses that can be prone

[2] Gender differences in numeracy skills using PIAAC have been documented in Battisti et al. (2023), Rebollo-Sanz and De la Rica (2022), and Christl and Köppl-Turyna (2020). Reiter and Spitzer (2025) link Austrian PIAAC and administrative data to show how career trajectories around parenthood vary for low- and high-skilled women.

[3] If education is not included as a control, we estimate a long-term child penalty of 0.22 standard deviations. Interestingly, controlling for education in the event study estimations for employment and earnings does not change the patterns, see Section 4.

[4] In fact, women are more likely to be employed in family-friendly occupations, especially the public sector, and this increases with parenthood (Goldin, 2014; Erosa et al., 2022; Pető and Reizer, 2021; Kleven et al., 2019b; Pertold-Gebicka et al., 2016).

[5] If an occupation with lower skill intensity also offers fewer opportunities for on-the-job training, skills might deteriorate even further. For example, Bertrand et al. (2010) investigate the careers of young professionals in the US. They find that gender differences in training (potentially affecting skills), career interruptions (largely driven by motherhood), and weekly hours play an important role in earnings differentials. The life-cycle model developed by Laun and Wallenius (2021) stresses the importance of human capital accumulation for the widening of the gender wage gap after parenthood.

to measurement error due to PIAAC's scaling procedure.[6] With this caveat in mind, we find small child penalties in both work- and non-work related assessment questions.

To assess the finding of an immediate decrease in numeracy skills for both mothers *and* fathers, we also look at parents' response behaviour in the survey. The literature from other disciplines such as neuroscience suggests that parenthood, especially in the early stages, is associated with increased stress and sleep deprivation, as discussed in Parfitt and Ayers (2014).[7] In turn, high levels of stress and reduced sleep can impair cognitive functioning and decision-making at least temporarily. This includes memory, attention, and executive functions, which are crucial for numeracy skills and test performance (Drummond and Brown, 2001; Minkel et al., 2012; Pilcher and Huffcutt, 1996). We test this hypothesis using the response behaviour of mothers and fathers in the PIAAC survey. Parents leave more numeracy questions unanswered, which could be interpreted as a measure of higher stress or reduced effort during the test, but there is again no significant difference between mothers and fathers. Additionally, we find no evidence for reduced attention or even distraction during the test since parents do not take much longer (or shorter) to complete the survey.

Our results show that larger drops in general labour market skills (and associated lower labour market returns) for mothers compared to fathers are unlikely to play a key role in the observed child penalties in employment and wages.[8] Instead, the findings are consistent with the view that child penalties in employment and wages are primarily driven by gender norms and expectations around gender differences in labour supply after childbirth and child care responsibilities. This implies that general training is unlikely to counteract child penalties in labour market outcomes. A more promising avenue might be to increase the availability and accessibility of family-friendly firms and childcare policies, or incentives for a more gender-balanced division of parental leave.[9] These could mitigate the overall loss of labour market experience and firm tenure as well as accumulation of specific human capital, which have all been shown to be associated with higher earnings (Burdett et al., 2020).[10] Additionally, better opportunities to balance family and work lives can preserve valuable firm-specific skills or occupation-specific requirements that can be transferred between firms.

The absence of a large child penalty in general labour market skills we observe in our data speaks against a more general theory of skill loss due to their reduced usage. Parental skill development after childbirth can be considered in a general framework of skill accumulation and depreciation (see e.g. Hanushek, 1986; Woessmann, 2016). Skill accumulation during education is followed by skill retention or expansion on the labour market. Hence, a longer absence from the labour market during early parenthood could be expected to lead to skill depreciation simply due to the associated reduced practice of certain skills.[11] This could, in principle, be true for all skills used on the job, i.e., cognitive as well as (work-related) social skills. In practice, we would expect skills that are not used in alternative activities to depreciate the most. Consequently, if the absence from the labour market after childbirth is associated with a lower usage of cognitive skills, e.g. in favour of increased usage of (general) social skills, this practical knowledge could decrease. In fact, changes in cognitive activity levels have been associated with concurrent changes in cognitive performance, suggesting that adopting or increasing such activities could have beneficial cognitive outcomes (Mitchell et al., 2012). While our results do not support this hypothesis of usage-dependent skill depreciation for general labour market skills, this pattern could be more prevalent for occupation- and firm-specific skills, which are not captured in our skill measures.

This paper's contribution sits within a large and growing literature on child penalties and determinants of gender inequality more broadly. Over the last few years, many empirical papers have measured child penalties in labour market outcomes across various countries (Kleven et al., 2024a).[12] Child penalties have been shown to be closely linked to societal norms as well as biological factors.

[6] The scores provided in PIAAC are constructed by OECD researchers using item response theory scaling procedures to account for the fact that respondents receive different subsets of questions with varying complexity (OECD, 2016). The OECD recommends not to use individual answers for any quantitative analysis and, in fact, they can rarely be found in research papers. While we follow these guidelines in our main analysis, we use raw responses to investigate different domains in this supplementary item-level exercise.

[7] Recent evidence from studies in economics also shows increased mental health burden after childbirth, possibly more pronounced for mothers (Ahammer et al., 2023; Barschkett and Bosque-Mercader, 2023).

[8] This is in line with evidence from Lemoine et al. (2025) who link parental leave policies in 19 European countries to skill differences between mothers and fathers from the Survey of Health, Ageing and Retirement in Europe (SHARE). On the one hand, they show that longer statutory leave durations are associated with lower numeracy skills of mothers, moderated by longer career breaks in the short run followed by lower employment in the long run. On the other hand, the modest size of these numeracy drops again suggests that skill depreciation plays a minor role in the motherhood penalty in other labour market outcomes.

[9] See Baertsch and Sandner (2025), Ciasullo and Uccioli (2024), Heckl and Wurm (2024), Karademir et al. (2024), Kuka and Shenhav (2024), Lim and Duletzki (2023) and Kleven et al. (2024b) and others for evaluations of such policies.

[10] On the one hand, insufficient family support can increase skill gaps, by making it harder to balance work and family responsibilities, potentially leading to occupational and labour supply choices that are more strongly affected by childcare considerations, especially for mothers. On the other hand, family-friendly policies can result in longer leaves, more asymmetry between partners, and potentially gender differences in measured cognitive performance (Edin and Gustavsson, 2008; Low and Sánchez-Marcos, 2015).

[11] See OECD (2013), Chapter 3, for a small overview of the related literature in cognitive and neuropsychology. Additionally, Hanushek et al. (2025) find evidence of usage-related skill evolution using the small panel extension from PIAAC in Germany. Unfortunately, there are not enough new parents in this panel dataset to systematically assess child penalties in a longitudinal framework.

[12] Kleven et al. (2024a) provides estimates of child penalties in employment for 134 countries around the world. Additionally, there is evidence from Bahar et al. (2025) for Australia, Berniell et al. (2021) for Chile, Casarico and Lattanzio (2023) for Italy, De Quinto et al. (2021) for Spain, Gallen (2024) for Denmark, Kim and Hahn (2022) for South Korea, Lebedinski et al. (2023) for Russia, Meng et al. (2023) for China, Sieppi and Pehkonen (2019) for Finland, and Sundberg (2024) for Sweden. Kleven et al. (2024a), Glogowsky et al. (2025), and Huttunen and Troccoli (2023) also investigate how child penalties have changed over time. Jensen (2024) uses rich Danish job vacancy data combined with register data to estimate returns to different types of skills (e.g. cognitive, social, and computer skills) on the labour market, focusing on gender differences. Again using administrative data from Denmark combined with a production function estimation, Gallen (2024) compares pay and productivity of men and women, also as a function of motherhood. While this approach is not directly comparable to child penalty estimates, it can inform the literature using broad measures of productivity.

As explored by Bertrand et al. (2015), gender norms significantly influence parental roles and responsibilities, thereby shaping the labour market skills and opportunities available to men and women.[13] The biological aspects of childbearing also play a key role in shaping the careers of women, as discussed by Goldin and Mitchell (2017) as well as the literature from neuroscience (see for example Parfitt and Ayers, 2014). To the best of our knowledge, we are the first to directly investigate the effect of parenthood on labour market skills for men and women using direct skill measures across many countries. To do so, we expand the approach developed in Kleven (2025) for estimating child penalties in repeated cross-sections to a single cross-section in an international framework, and show that characteristics of the respective outcome variable can be very important in these settings. The cross-country data enhance the external validity of the results as the patterns we describe are observed across a broad set of countries.

Our paper also adds to the larger discussion on determinants and consequences of skill depreciation. While we are not aware of evidence on changes in cognitive skills driven by parenthood, there is a literature on skill depreciation as a consequence of (other) absences from the labour market. Cohen et al. (2025) find no significant declines in cognitive skills while workers remain unemployed, in contrast with Edin and Gustavsson (2008) who find skill depreciation during non-employment to be economically important. Dinerstein et al. (2022) use administrative data for teachers in Greece and find significant skill depreciation from non-employment.[14] However, there are clear differences between the experience of parenthood and other episodes of non-employment. Besides the potential employment interruption, childbirth comes with many other changes for parents, including reduced working hours and flexibility, and a deterioration in sleep quality. We contribute to this literature by providing evidence on changes in measured cognitive performance around the birth of the first child. This is crucial to grasp the nature of child penalties in labour market outcomes, as general skills are an essential component of labour market trajectories. More generally, Hanushek et al. (2025) show that age-related skill decline is strongly related to skill use, but these patterns are less visible for females where even high usage of numeracy skills does not prevent skill depreciation at ages 40–65. This supports our findings that skill usage seems to play a smaller role for gender gaps in skills.

2. Data

PIAAC. The Survey of Adult Skills is a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). It is a large-scale international survey administered between 2011 and 2017.[15] PIAAC provides standardised imputed measures of skills for individuals aged 16–65 in numeracy, literacy, and problem-solving,[16] and is comparable to the well-known Programme for International Student Assessment (PISA), which surveys adolescents. PIAAC aims to uncover competencies that are required for the advancement in the workplace and participation in society.

Following the guidance of the OECD and the methodological literature, we use all ten plausible values provided by the OECD per domain for each respondent. These plausible values are generated using item response theory on the scores of individual questions. They are constructed to provide reliable population-level estimates by accounting for both item-level uncertainty and respondent characteristics. Using actual responses generally introduces measurement error due to the sampling design of the PIAAC test, where different respondents answer different questions. Raw scores hence do not adjust for item difficulty, booklet design, or differential item functioning, and are therefore not comparable across individuals or populations (OECD, 2016).[17]

We standardise the skill measures to have mean zero and standard deviation one within each country.[18] The focus of our analysis are numeracy skills due to their importance for labour market outcomes, large average gender gaps, and comparability across countries (Hanushek et al., 2015), but we also show results for the other dimensions tested in PIAAC: literacy and problem-solving.[19]

Fig. 1 plots the distribution of numeracy scores for men and women across countries. While score distributions of men and women substantially overlap for all respondents (panel a) as well as for parents (panel b), average numeracy scores are higher for men in both samples. The average gender gap is 0.188 standard deviations (sd) for all respondents, and 0.237 standard deviations among parents. Hence, gender gaps in numeracy scores are pervasive and seem to be especially pronounced for parents.

[13] Similar evidence can be found in Jessen (2022) for cultural differences between East and West Germany and in Kleven (2025) for the United States.

[14] Other related papers include (Ortego-Marti, 2017), who use PSID data to document differences in skill depreciation across industries and occupations in the United States, and theoretical considerations of skill loss after job loss from Lalé (2018) and Jackson and Ortego-Marti (2024).

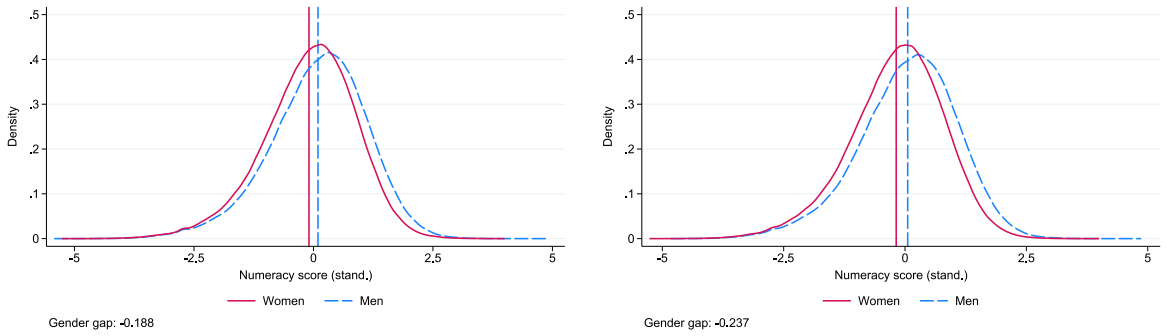
[15] The second wave of PIAAC was collected in 2022–2023 and is set to be released in December 2024. The full list of participating countries and the survey schedule can be found at https://www.oecd.org/en/about/programmes/piaac.html (last accessed on November 11, 2025).

[16] Numeracy is defined as 'the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life'. Literacy is defined as 'the ability to understand, evaluate, use, and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential'. Problem solving in technology-rich environments is described as 'using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks'. Sample questions of PIAAC are available here: https://www.oecd.org/en/about/programmes/piaac/piaac-released-items.html (last accessed on November 11, 2025).

[17] This concern is echoed in the recent methodological literature. Among others, Khorramdel et al. (2020) show that raw scores derived from matrix-sampled assessments like PIAAC are biased and unreliable. Relatedly, Jewsbury et al. (2024) demonstrate that using raw or point-estimate scores instead of plausible values leads to underestimating standard errors and invalid inference. Virtually all prior research using PIAAC that we are aware of, including Hanushek et al. (2015) and Falck et al. (2021) among many others, relies on these imputed values, ensuring comparability across studies.

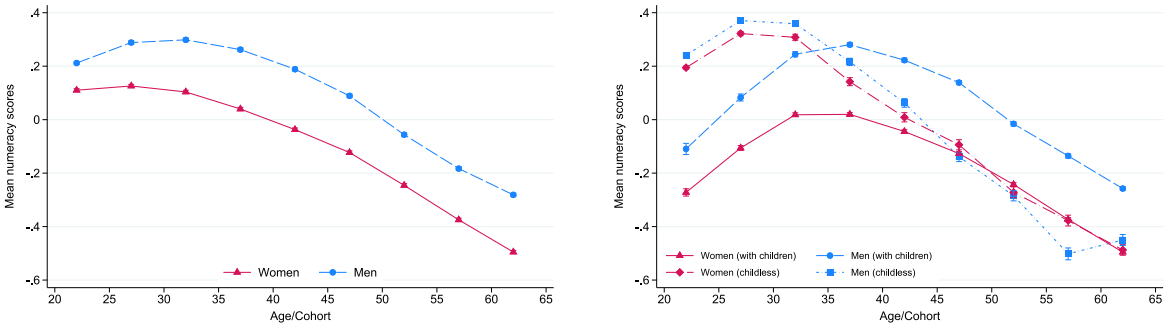
[18] By using country dummies in our later estimations, we effectively conduct within-country comparisons, i.e. we abstract from international differences. Pooling all available countries into one dataset allows us to gain statistical power for estimating child penalties in a setting where each country individually has a relatively low number of recent parents (see Appendix Table A.1).

[19] While literacy was tested in all PIAAC countries, as is the case for numeracy, problem-solving in technology-rich environments was only assessed in 26/29 of the countries we use in our analysis.



(a) All (b) Parents

Fig. 1. Distribution of numeracy scores by gender.
Notes: Weighted kernel density plot of standardised numeracy scores for men and women aged 20 to 65. All ten plausible values are used for each respondent. Standardisation by country uses individuals' sampling probability. Panel (a) contains all respondents ($N = 171,778$) and panel (b) restricts the sample to parents ($N = 108,014$).
Source: PIAAC international PUF.



(a) By age (b) By age and parental status

Fig. 2. Numeracy scores by age, gender, and parental status.
Notes: Mean standardised numeracy scores by age (in five-year intervals) for men and women aged 20 to 65. Confidence intervals for each data point are added. All ten plausible values are used for each respondent. Standardisation by country uses individuals' sampling probability. Panel (a) contains all respondents ($N = 171,778$) and panel (b) only shows respondents with information on parental status ($N = 157,399$).
Source: PIAAC international PUF.

Fig. 2 shows average numeracy skills of men and women in five-year age intervals. A gender numeracy gap is visible for women and men of all age groups, but it is slightly smaller for younger respondents up to the age of 35 (panel a). Parents at ages 20–35 have consistently lower numeracy scores than their childless counterparts suggesting negative selection into parenthood in terms of skills for these individuals (panel b). Fathers from the age of 40 onwards have higher average numeracy levels than childless adults whereas female parents of all ages stay below the average scores of the childless. Most interestingly, we observe a gap in average numeracy scores for parents but not for childless individuals which further motivates investigating the role of parenthood. The PIAAC survey includes rich background and labour market information, such as education, current and previous work experience, household composition including the presence of children, and migration status, among others. This allows for a thorough investigation of individuals' skills and their associated labour-market trajectories. Most relevant for this paper is the information about children. PIAAC records both the number of children and their age (but not their gender), which allows us to calculate the distance (in years) between the survey year and the year of birth of their first child.

Table 1 presents average numeracy scores and ages at first childbirth by gender for the 29 countries that we use in our analysis.[20] All countries have a gender gap in raw numeracy scores in favour of men, except for Kazakhstan. The age at which men and women on average have their first child ranges from 22 (for women in Ecuador and Peru) to 30 (for men in Greece, Italy, Japan, the Netherlands, and Singapore). The average age gap between mothers and fathers across countries ranges between two and five years.

[20] As described more in detail in footnote and in Section 3, we use 29 of the 35 surveyed countries with publicly available data due to the availability of background characteristics that are essential to our matching procedure.

Table 1
Numeracy scores and age at birth of first child.
Source: PIAAC international PUF.

Country	Average numeracy score			Average age at first birth		
	Men	Women	Gap (M-W)	Men	Women	Gap (M-W)
Belgium	288	272	16	28	26	2
Chile	217	196	21	25	23	2
Czech Republic	280	271	9	26	23	3
Denmark	284	273	10	28	26	2
Ecuador	190	181	9	25	22	2
Estonia	276	270	6	25	23	2
Finland	288	278	10	28	26	2
France	260	249	11	28	25	3
Greece	256	249	7	30	25	5
Hungary	274	271	2	27	24	3
Ireland	262	250	12	28	26	2
Israel	257	246	11	28	25	3
Italy	252	242	11	30	26	4
Japan	294	282	12	30	27	3
Kazakhstan	247	247	−0	26	24	2
Korea	269	258	10	29	26	3
Lithuania	268	266	2	26	24	2
Mexico	216	206	10	25	23	3
Netherlands	289	272	17	30	27	3
New Zealand	278	265	12	28	26	2
Norway	286	271	15	28	25	2
Peru	187	172	16	26	22	3
Poland	261	259	2	27	24	3
Singapore	265	251	14	30	27	3
Slovak Republic	277	275	2	26	23	3
Slovenia	260	255	4	27	24	3
Spain	252	240	12	29	26	3
Sweden	286	272	13	28	26	3
United Kingdom	269	254	14	28	25	2
Total: 29	262	251	10	27	25	3

Notes: Table shows summary statistics for men and women in the PIAAC sample for the 29/35 countries we use in our analysis. Average values are calculated using sampling probabilities. Numeracy scores are raw, non-standardised values. Age is only available in five-year brackets for Hungary, New Zealand, and Singapore, see Appendix Table A.1.

In order to estimate child penalties in cross-sectional data we generate a pseudo-panel of the outcomes of interest for parents, following Kleven (2025). Given that we do not observe parents before and after childbirth (but rather only at one specific point in time), we use outcomes of observationally similar respondents that are observed either before or after childbirth. As a first step, we identify first-time parents and their respective distance to childbirth through the age of their (oldest) child. This allows us to compare parents from event times $t = 0$, i.e. right after childbirth, to those who currently are at any positive event time $t > 0$, i.e. t years after the birth of their first child. We assume that these individuals are comparable, at least on all observables and unobservables that have led them to decide to have children. For the years prior to childbirth, this is more complicated because childless individuals have yet to realise their fertility decisions. Kleven (2025) identifies younger individuals who are similar on a set of pre-determined characteristics and uses their observed outcomes as proxies for the pre-birth periods of new parents. The underlying assumption is that the similarity on the matching observables identifies those respondents who will have children in the future.

The resulting matching procedure of individuals to their surrogate observations in periods prior to childbirth requires information on a set of characteristics used to predict the selection of childless individuals into parenthood (see Appendix Table A.1). In particular, we use the age of a respondent to identify younger individuals who are $t < 0$ periods before childbirth. A 'continuous' age variable for respondents is only available for 26 of the 29 countries we use. Three countries report respondents' ages in 5-year categories.[21] Kleven (2025) uses gender, education, marital status, state of residence, and race as matching variables in the US context. We adapt this set of pre-determined characteristics to the international context and to the information contained in PIAAC. The respondents' gender is available in all countries and contains two categories: female and male. For education, we use a variable that distinguishes between six levels: 'lower secondary or less', 'upper secondary', 'post-secondary/non-tertiary', 'tertiary professional

[21] Five countries from the original PIAAC survey (Austria, Canada, Germany, Turkey, and the US) are omitted in our analysis because they only contain the age of *children* in age brackets, which makes it impossible for us to determine the relative distance to childbirth ($t \geq 0$) for their parents. Additionally, we omit Russia due to data irregularities as documented in the Data Appendix of Battisti et al. (2023).

degree', 'tertiary bachelor degree', and 'tertiary master/research degree'. Finally, instead of marital status we observe whether an individual lives with their partner (yes/no), the country of residence, and whether someone was born in the country they currently live in (yes/no). Appendix Table A.1 shows the number of first-time parents we observe in each country, split by gender.[22] It also contains the median level of education and the shares of individuals living with their partner or being born abroad for our estimation sample.[23]

SOEP. In order to validate our main empirical approach, we use the German Socio-Economic Panel (SOEP, Goebel et al., 2019), an annual longitudinal household survey running since 1984 that currently includes around 38,000 respondents aged 18–65. SOEP contains information on labour market outcomes and detailed socio-economic characteristics. Because SOEP is a long-running panel study and many respondents have been part of the survey for decades, we observe a large number of births. More importantly, we are able to observe parents at all event times of interest ($-5 \leq t \leq 10$). This allows us to validate our empirical approach for the PIAAC data by using the SOEP to compare child penalties based on i) actual panel data, ii) a pseudo-panel with repeated cross-sections as in Kleven (2025), and (iii) a single cross-section.

3. Empirical approach

We follow Kleven (2025) and Kleven et al. (2024a) in generating a *pseudo-panel* to analyse child penalties in cross-sectional data. Given the availability of different background characteristics in the SOEP and the PIAAC data, we use slightly different matching procedures.

Validation using SOEP. We start with a validation of our empirical approach using the SOEP panel dataset before discussing the estimation of our outcomes of interest with PIAAC data. We focus on employment and monthly earnings as child penalties for these labour market outcomes are well-known. As a gold standard, child penalties are estimated using panel data where both pre- and post-birth observations of (becoming) mothers and fathers are included. In the standard estimation, the outcome is regressed on event-time dummies (years relative to first birth, $\mathbb{I}[j = t]$). Additionally, age ($\mathbb{I}[k = age_{is}]$) and calendar year ($\mathbb{I}[y = s]$) dummies are included to partial out life-cycle effects and general time trends or shocks in outcomes. For instance, Kleven et al. (2019b) estimate the following equation separately for men and women (g) in survey year s at event time t[24]:

$$y_{ist}^{g} = \sum_{j \neq -2} \alpha_j^g \cdot \mathbb{I}[j = t] + \sum_k \beta_k^g \cdot \mathbb{I}[k = age_{is}] + \sum_y \gamma_y^g \cdot \mathbb{I}[y = s] + \epsilon_{ist}^g \tag{1}$$

Child penalties for labour market outcomes obtained from equation (1) are the basis for our validation. In an intermediate step, we follow the matching procedure outlined by Kleven (2025) and treat the SOEP data as if it was a repeated cross-section to estimate pseudo-event studies. Positive event times, i.e. after the birth of the first child, are observed in cross-sectional data whenever they contain information on the age of children, and specifically of the oldest child. This way, we can pin down the event time after childbirth for all parents and use these parents for estimations in positive event times. To identify plausible *future* parents, we match new parents (i.e. in $t = 0$) to observationally similar younger individuals in prior survey years who are assumed to be suitable *surrogate observations* for becoming parents based on their characteristics, which means that outcomes of these individuals should follow similar paths as those of actual becoming parents. Besides gender, we match on educational attainment, being born in Germany, living in East or West Germany, cohabitation status, age, and survey year.[25] The estimation is again based on equation (1). Pseudo-event studies rely on the assumption that matching on the set of characteristics reliably identifies comparable future parents. As for the true (panel) event studies, life-cycle effects and annual shocks can be netted out in the estimation by using age and survey year dummies.

Finally, we impose the same data structure as in PIAAC and treat SOEP as if it was a single cross-section. In the matching process, this implies matching new parents (i.e., in $t = 0$) with similar individuals in the *same* survey year instead of prior survey years. In the empirical implementation, this means that $\sum_y \gamma_y^g \cdot [y = s]$, the term associated with the year dummies in Eq. (1), is dropped, and that we are unable to separately identify age and cohort differences in our estimation. This implies that we assume away cohort differences once the controls we include are accounted for.

In Fig. 3, we plot the α_j event-time coefficients from estimating equation (1) for employment and monthly earnings, using the three different procedures described above. The upper row shows coefficients for the true panel, the middle row for the pseudo-panel, and the bottom row for estimates based on a single cross-section.[26] Estimates obtained using the true panel and the matched pseudo-panel are visually indistinguishable from one another. The estimates using a single cross-section are inevitably noisier as the

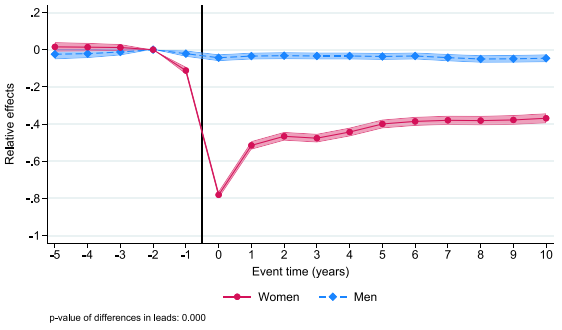
[22] The number of first-time parents we manage to match (1079) is only slightly smaller than the total number of first-time parents in the full international PIAAC sample (1193) and similarly distributed among the countries, which means that we can exclude large sample selection bias from matching.

[23] Given the relatively small number of first-time parents for each country, we focus on the aggregate sample using all available observations. We acknowledge that there are cross-country differences in the composition of first-time parents on observable but potentially also unobservable characteristics. Due to our exact matching procedure within gender and the inclusion of country fixed effects, this is unlikely to bias our results.

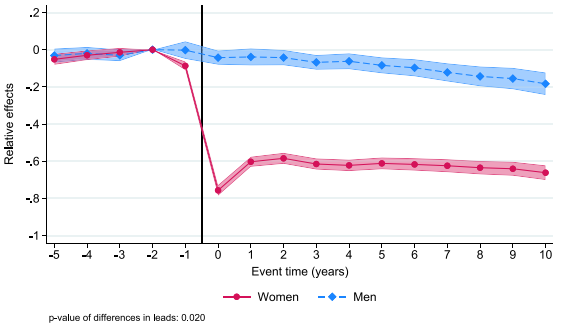
[24] In line with several other papers in the literature, we change the reference period to event time $j = -2$ (compared to $j = -1$ in Kleven et al., 2019b) as in the year immediately prior to first birth some adjustments related to pregnancy may have already occurred.

[25] The last two variables are aligned such that the surrogate observations in, e.g., $j = -2$, are two years younger and observed two years before those with a birth in $j = 0$.

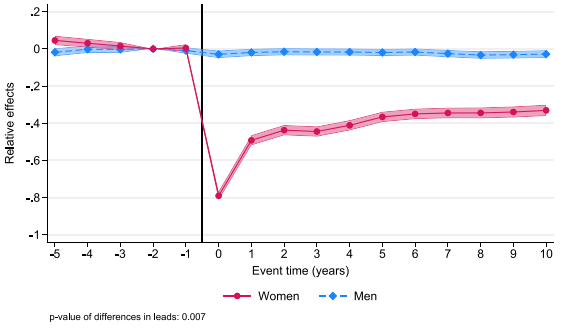
[26] The single cross-section is shown for the year 2014, the average survey year of PIAAC. Estimates for each year from 2005 to 2016 are presented in Appendix Figures A.1 and A.2.



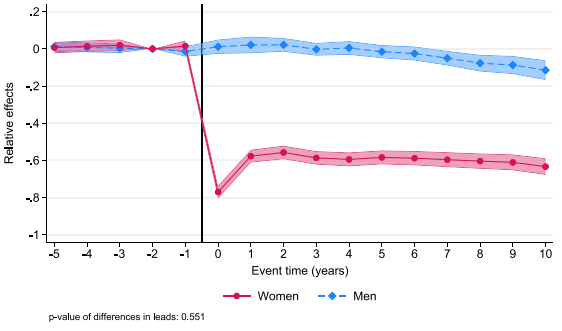
(a) True panel: employment



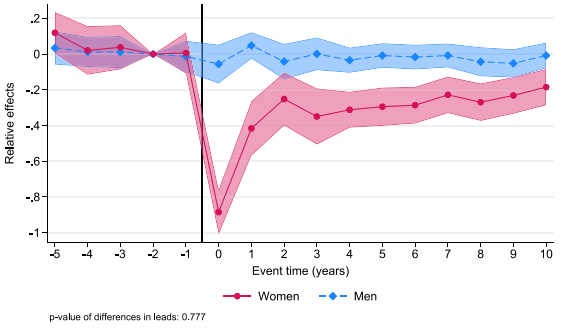
(b) True panel: monthly earnings



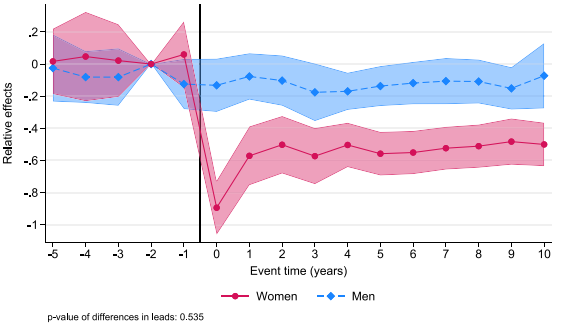
(c) Pseudo-panel: employment



(d) Pseudo-panel: monthly earnings



(e) Single cross-section: employment

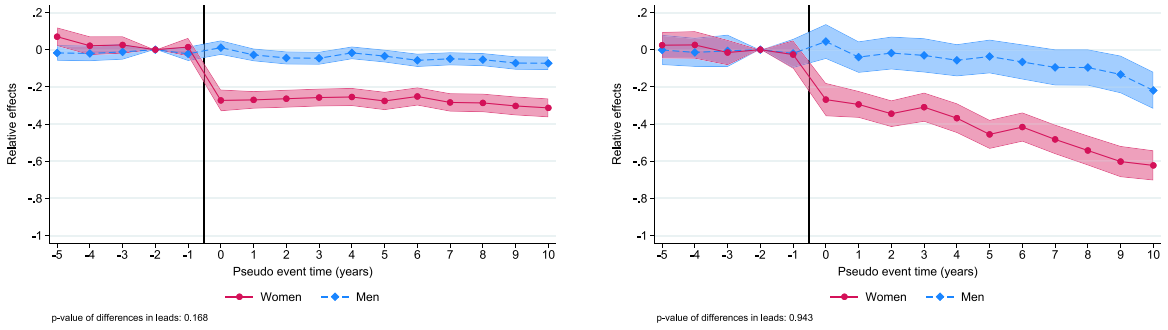


(f) Single cross-section: monthly earnings

Fig. 3. Child penalties in labour market outcomes—SOEP validation.
Notes: Plots show the event-time coefficients α_j obtained from estimating equation (1). The upper row is based on a true panel, the middle row is based on a pseudo-panel where the pre-birth observations are obtained via matching, and the bottom row shows estimates from a single cross-section in 2014. Shaded areas represent 95% confidence bands. Appendix Figures A.1 and A.2 show annual estimates from 2005 to 2016.
Source: SOEP-Core, v37.

sample size drops dramatically when using only one survey year. Nevertheless, the patterns look reassuringly similar, and document a child penalty for mothers in both employment and monthly earnings and little to no difference for fathers.

Single cross-section using PIAAC. After showing how the estimation of child penalties in a panel can be adapted to a single cross-section, we now proceed to our estimation of interest, i.e. child penalties in numeracy skills from PIAAC. The matching procedure is slightly different due to the availability of background characteristics as well as the international setting. As in SOEP, we first identify individuals at event time $t = 0$, i.e. those where the first child of respondents was born in the 12 months before the PIAAC survey was conducted. For these individuals, we again create a pseudo-panel for event times $-5 \leq t \leq -1$ through the matching procedure



(a) Employment (b) Monthly earnings

Fig. 4. Child penalties in labour market outcomes—PIAAC validation.
Notes: Plots show the event-time coefficients α_j obtained from estimating equation (2). The sample in panel (a) consists of all countries listed in Appendix Table A.1. Panel (b) omits Hungary, Peru, and Singapore as these contain no earnings information. Sweden reports earnings in deciles and we use the midpoint per decile. Shaded areas represent 95% confidence intervals.
Source: PIAAC International PUF.

described above. We match on age, gender, and education of an individual as pre-determined characteristics. As the PIAAC survey does not record respondents' marital status, we have to rely on cohabitation with the partner as a proxy for marriage.[27] Instead of race, as used by Kleven (2025), we use a dummy for whether a respondent was born in the country they currently live in, and instead of U.S. states (Kleven, 2025) or rural/urban living area (Kleven et al., 2024a), we use the country of residence. Following this procedure, we are able to match 1079 current first-time parents (603 men and 476 women, see Appendix Table A.1) from 29 countries to potentially multiple surrogate observations from younger childless individuals.[28]

Our slightly adapted estimation equation is then:

$$Y^g_{itc} = \sum_{j\neq -2} \alpha^g_j \, \mathbb{I}[j = t] + \sum_k \beta^g_k \, \mathbb{I}[k = age_i] + \mu_c + v^g_{itc} \tag{2}$$

where Y^g_{itc} measures our outcome (employment, earnings, skills) of individual i of gender g at event time t in country c. The α^g_j for $j \neq -2$ are the coefficients of interest, and estimate changes in the outcome before and after childbirth, using $t = -2$ as the reference period. The β^g_k capture the influence of age, and we add country dummies μ_c to focus on within-country comparisons. The country dummies absorb any relevant cross-country differences, such as childcare availability, parental leave legislation, gender norms, occupational flexibility, or industry structure which could affect both the timing of childbirth and the outcomes studied. Since we use data from a single cross-section, we cannot include survey year indicators, which would account for cohort differences and idiosyncrasies of survey years.[29] Our estimation hence implicitly assumes no skill differences between individuals of the same age at different points in time, at least for the age range of the individuals we are using in the pseudo-panel.[30] The event-time coefficients are statistically identified due to variation in age at first birth across individuals and across countries.

Fig. 4 shows coefficients from estimating equation (2) using PIAAC data for employment (panel a) and earnings (panel b). Both outcomes move in parallel before pregnancy and diverge to the disadvantage of women right after the birth event.[31]

4. Results

4.1. Parenthood and labour market skills

Fig. 5 plots the gender-specific event-time dummies α^g_j based on equation (2) using numeracy skills as our outcome. In the estimation, we use all ten plausible values of the numeracy score provided in the data and cluster standard errors at the respondent level. The dependent variable is standardised such that coefficients can be interpreted in standard deviations. For (future) mothers and fathers, we observe similar pre-birth trends and a sustained drop in the numeracy score up to ten years after childbirth. The

[27] Differences between cohabitation and marriage are likely to depend on the cultural norms of a country. Whether or not both marriage and cohabitation are suitable variables for the matching procedure strongly depends on whether and when individuals tend to marry and/or cohabit prior to the birth of their first child.

[28] We use the average numeracy score of all matched observations in case of multiple matches.

[29] With multiple time periods, one could also account for time-varying characteristics, e.g. when child care is rapidly expanded within a short time period.

[30] Using the German panel extension of PIAAC ('PIAAC-L'), Hanushek et al. (2025) show that skill evolution is indeed strongly related to age progression, in particular depending on the usage of skills on the job.

[31] The child penalty in employment using the PIAAC data is 0.24, which is comparable to the average child penalty of 0.31 estimated in Kleven et al. (2024a) for the same set of countries.

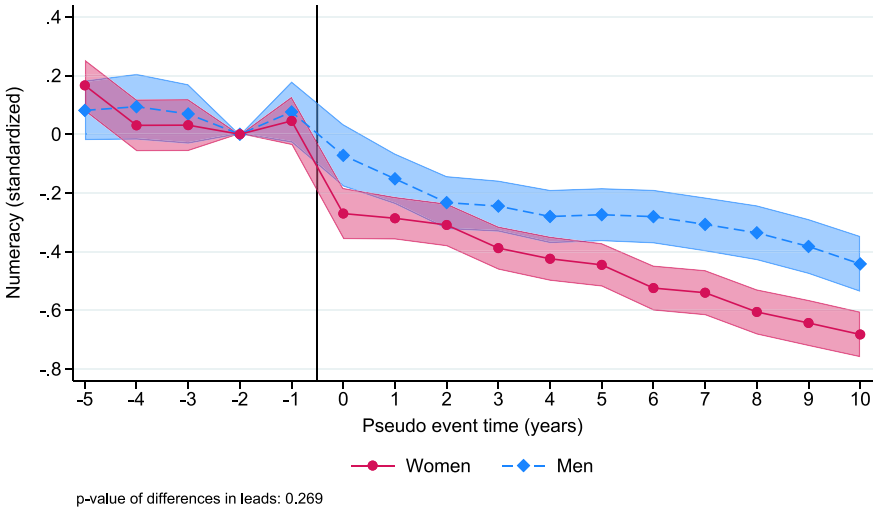


Fig. 5. Child penalties in numeracy scores (without matching controls).
Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2). The dependent variable is the standardised numeracy score. Shaded areas represent 95% confidence intervals. The corresponding summary estimates are shown in Appendix Table A.4.
Source: PIAAC international PUF.

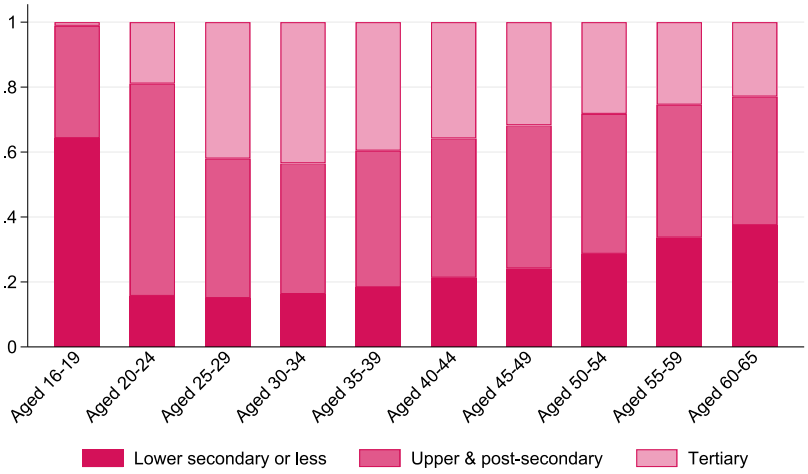


Fig. 6. Differences in education levels between PIAAC cohorts.
Notes: Figure shows education levels by age groups of all PIAAC respondents.
Source: PIAAC international PUF.

drop is larger for mothers with the individual event time dummies being significantly different from those of fathers around the time when children enter primary school. In contrast to estimates for labour market outcomes from the existing literature and our estimations in Figs. 3 and 4, fatherhood seems to be associated with a significant reduction in numeracy skills.

The overall decreasing pattern of numeracy skills after childbirth for both mothers and fathers raises the concern whether we might be picking up systematic skill differences between cohorts. In particular, skill differences might be related to changes in overall education levels over the last decades. Especially women in the cohorts we observe in our sample have caught up in terms of educational attainment, both compared to men and to previous cohorts (see e.g., Charles and Luoh, 2003; Eurostat, 2020), and are now more likely to hold college degrees compared to men in most richer countries (Kleven and Landais, 2017; Goldin, 2024; Becker et al., 2010). Appendix Table A.2 shows that even though our estimation dataset contains a relatively wide range of ages for each event time, naturally respondents in later event times tend to be older which implies that on average later event times contain individuals from earlier cohorts. Fig. 6 additionally shows that there are substantial differences in education levels between the cohorts in PIAAC. While the education patterns for respondents aged 16–24 can most likely be explained by them still being

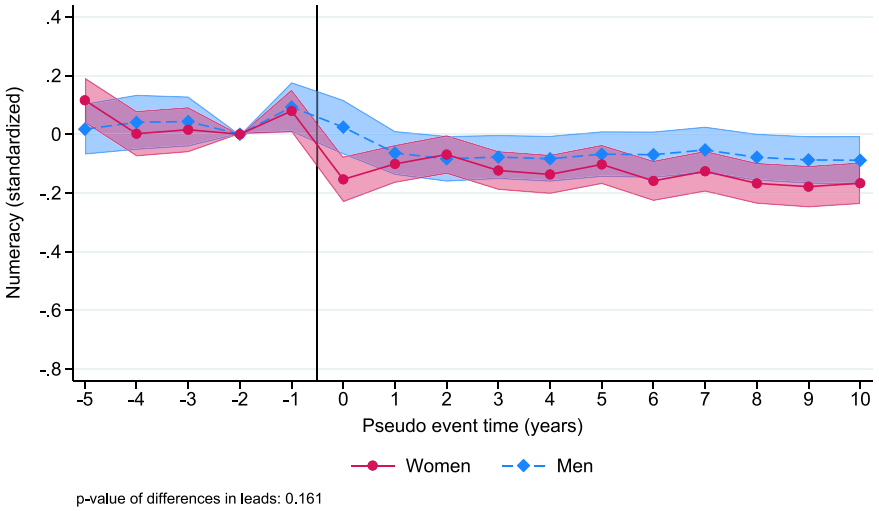


Fig. 7. Child penalties in numeracy scores (with matching controls).
Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2) together with controls for living with the partner, being born in the survey country, and education levels. The dependent variable is the standardised numeracy score. Shaded areas represent 95% confidence intervals.
Source: PIAAC international PUF.

in education, older respondents have almost surely completed their formal education. Hence, the decreasing share of respondents with tertiary education in earlier cohorts rather seems to reflect cohort differences in education levels.[32]

Consistent with this view, Fig. 7 shows that controlling for education along with the other variables used in our matching procedure significantly changes the child penalty estimations for numeracy skills.[33] We still observe a slight drop in numeracy skills compared to the period before childbirth, potentially due to sleep deprivation or stress affecting the performance on the PIAAC test—or an actual reduction in these skills. Mothers' point estimates are, with one exception, below those of fathers, but the longer-term coefficients are not statistically different between mothers and fathers. Once we pool the short- and long-term effects ($t \in (0, 4)$ and $t \in (5, 10)$, respectively) in Table 2, we see that mothers experience a larger drop of 0.069 standard deviations (0.184 sd, column 2, compared to 0.115 sd, column 1). The difference is statistically significant at the 10% level.

The point estimate and standard errors allow us to rule out long-term gender differences in numeracy scores around parenthood of more than 0.139 sd, which following Hanushek et al. (2015) would correspond to wage differences of 2.5%.[34] If we combine this with the long-term child penalty in monthly earnings of 24% reported in Appendix Figure A.5 and make the simplifying assumption that these lower numeracy scores affect wages but not hours worked, this implies that the upper bound of our estimates (2.5%) can account for at most around 10% of child penalties in earnings. Considering our point estimate as the true post-childbirth difference in numeracy between mothers and fathers, reduces this share to 1%/24% = 5.2%.

While educational attainment is likely to be the most important source of heterogeneity between cohorts in this context, given the cross-sectional nature of our dataset, we are not able to control for cohort differences driven by unobservables.

Child penalty estimates for other labour market outcomes do not depend as strongly on the inclusion of the matching controls. Appendix Figure A.5 shows child penalties in PIAAC measures of employment and earnings as in Fig. 4, additionally controlling for education, cohabitation, and migration status as described above. Including these variables does not change the general picture of the child penalties, but it reduces the size of the penalty for both outcomes.[35] Hence, it seems that general trends in education affect skill levels much more than wage levels or other labour market outcomes.

Fig. 8 presents results for literacy and problem-solving skills including the matching controls as in our preferred specification. As expected, due to the strong correlation of the different skill measures (see Appendix Figure A.6), the coefficients for literacy and

[32] Additionally, we might think that education can capture the latent ability part in the PIAAC numeracy measure. Hence, correcting for education in our estimation might allow to isolate the practical part of numeracy skills related to their use on the job.

[33] This change is entirely driven by education levels as can be seen in Appendix Figure A.3, which shows how the results depend on the inclusion of each control separately.

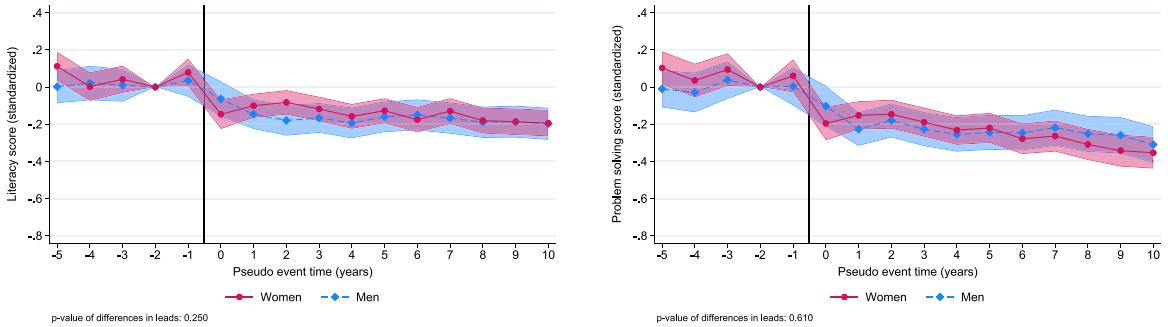
[34] In Appendix Figure A.4, we re-estimate returns to skills using our sample of (becoming) parents and without Hanushek et al. (2015)'s restriction to full-time workers. Compared to their average returns to numeracy skills of 18 percent, for our sample of (becoming) parents we identify 17 and 16 percent, for women and men respectively, as average returns to a one standard deviation higher level of numeracy scores. As our estimates of returns to skills are slightly smaller than those of Hanushek et al. (2015) (depending on the event-time), with our numbers an even lower share of wage differences can be accounted for by skill differences around parenthood. We find no evidence for differential returns by pseudo-event time.

[35] Comparing child penalty estimates of labour market outcomes using SOEP panel data shows only minor differences when pre-determined individual characteristics are included in the estimation.

Table 2
Summary estimates for child penalties in numeracy (with matching controls).
Source: PIAAC international PUF.

	Men (1)	Women (2)	Women-Men (3)
Pre-birth	−0.0130	0.0003	0.0133
	(0.0291)	(0.0251)	(0.0385)
Short-term effect	−0.1113***	−0.1496***	−0.0383
	(0.0254)	(0.0215)	(0.0333)
Long-term effect	−0.1146***	−0.1835***	−0.0689*
	(0.0270)	(0.0232)	(0.0356)
Observations	13,624	17,693	31,317

Notes: Table shows summary estimates for child penalties in numeracy scores corresponding to event-time coefficients presented in Fig. 7. The pre-birth period contains event times −5 to −3, the short-term effect contains event times 0 to 4, and the long-term effect pools event times 5 to 10. The omitted category is two years before birth. Standard errors clustered at the individual level in parentheses, * < 10% ** < 5% *** < 1%.



(a) Literacy score (b) Problem-solving score

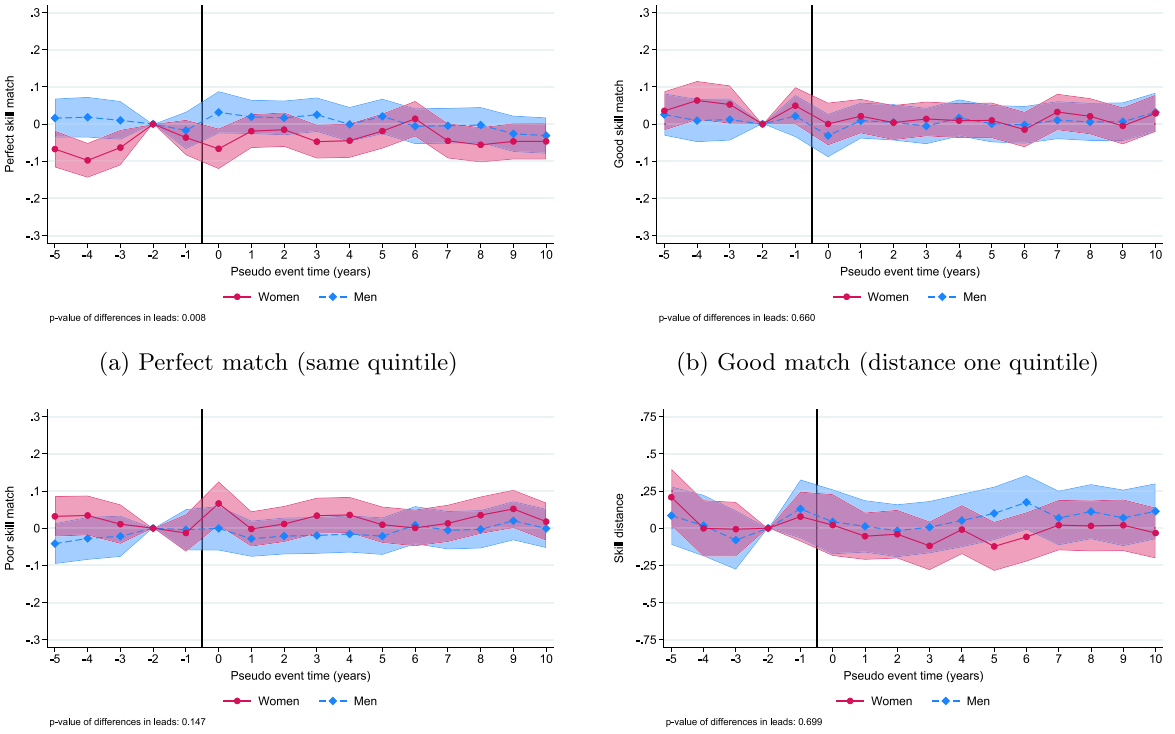
Fig. 8. Child penalties in literacy and problem-solving scores (with matching controls).
Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2) together with controls for living with the partner, being born in the country, and education levels. The dependent variables are the standardised literacy and problem-solving scores. Problem solving was not assessed in France, Italy, and Spain. Shaded areas represent 95% confidence intervals.
Source: PIAAC international PUF.

problem-solving scores reveal very similar patterns: no pre-birth differences, a drop for both parents right after childbirth, and no pronounced gap between mothers and fathers in the long run. The long-term estimates of around 0.2 standard deviations for literacy and up to 0.31 standard deviations for problem solving are shown in Appendix Table A.5. The long-term estimate on problem-solving is larger for women compared to the other two outcomes, but not statistically different to the drop for fathers and we can rule out increases on the long-term gender differences of more than 0.09 and 0.15 standard deviations.

Next, we explore heterogeneities along respondent characteristics. In Appendix Figure A.7, we show separate event study estimates for those with and without a college degree and by age at first birth, where in the latter case we conduct a median split within countries. Panel (a) reveals that the small long-term gender difference in numeracy scores after childbirth seem to be driven by the college-educated (although no point estimates between and men and women differ from one another) and there are no gender differences between respondents without a degree. The heterogeneity by age at first birth shows a larger drop in skills for both genders among younger parents, who on average would still experience larger skill increases at this age (Hanushek et al., 2025). In contrast, among older parents skills remain quite stable after childbirth. As discussed before, a caveat to this analysis is, that we are empirically unable to disentangle age and cohort effects. The age split is thus similar to a cohort split, where younger individuals are those born in later cohorts.

4.2. Implications for skill (mis-)match

Even though the previous analyses have shown at best evidence for small differences in skill development of mothers and fathers, we may still be concerned about post-childbirth selection of parents into jobs that do not correspond well to their skill set. If mothers are more likely to work in jobs that do not match their skills, in addition to working fewer hours and thus reaping lower returns to experience (Blundell et al., 2016), this could be another reason why not only employment but also hourly wages often drop for mothers after childbirth.



(a) Perfect match (same quintile)

(b) Good match (distance one quintile)

(c) Poor match (distance more than one quintile)

(d) Cardinal measure of skill distance

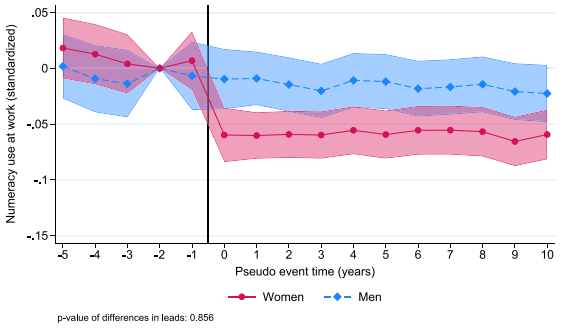
Fig. 9. Child penalties in numeracy skill mismatch.
Notes: Figure plots the event-time coefficients α_j obtained from estimating equation (2), together with controls for living with the partner, being born in the country, and education levels. The dependent variables are distances to the country- and occupation-specific skill requirements as described in Section 4.2. Shaded areas represent 95% confidence intervals. The corresponding summary estimates are shown in Appendix Table A.6.
Source: PIAAC international PUF

To study the dynamics of skill mismatch, we closely follow recent work by Bandiera et al. (2024) to create a measure of skill mismatch within the PIAAC dataset. Using information on skill use at work elicited in the data and weighted by the difficulty of these specific tasks, Bandiera et al. (2024) calculate country-specific numeracy (and literacy) skill requirements for each occupation. Appendix Figure A.8 shows average numeracy skill requirements by 1-digit ISCO occupations (in the analysis we use 2-digit ISCO occupations) with broadly expected patterns: managers and professionals have the highest skill requirements, machine operators and elementary occupations the lowest. The average numeracy score is increasing with higher skill requirements and the correlation coefficient between the average numeracy score and skill requirement is large ($\rho = 0.89$).

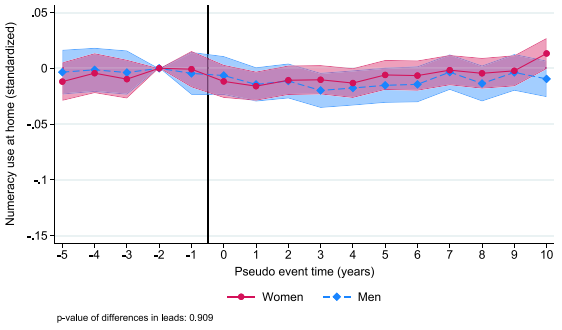
Occupations are subsequently mapped into country-specific quintiles of skill requirements, and similarly PIAAC respondents are assigned to country-specific quintiles based on their numeracy scores. Skill (mis-)match is then defined as the distance between the numeracy score quintile and the skill requirement quintile of the current occupation. If a worker is within the same quintile of the occupation-specific average, a match is considered 'perfect'. Instead, it is categorised as 'good' if the two measures are at most one quintile apart, and 'poor' if they are more than one quintile apart. A continuous measure using the Euclidian distance between individual skill use and job skill requirements complements their analysis. Appendix Figure A.9 shows that on average skill (mis-)match between (all) women and men is relatively similar in the PIAAC data, but with a somewhat larger share of perfect job-skill-requirement-numeracy-score matches for men (1.9 percentage points or 7% more perfect matches, statistically significant at the 1% level).

Fig. 9 plots the α_j coefficients of equation Eq. (2) for these four measures of skill mismatch, summary coefficients are reported in Appendix Table A.6. We find no evidence for long-term effects on skill match. Hence, a skill mismatch after childbirth does not seem to drive the child penalties in commonly analysed labour market outcomes, at least for employed individuals as we do not observe selection of mothers or fathers into occupations with different skill requirements after childbirth.[36]

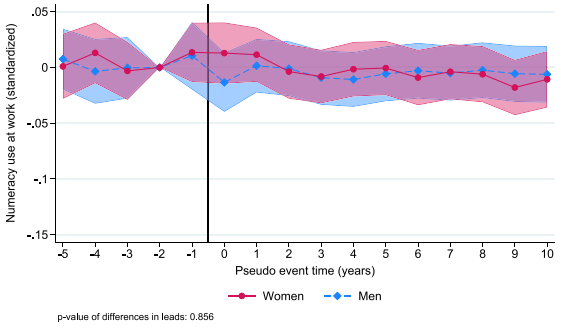
[36] Similarly, we find no evidence for mothers or fathers working more often in more highly-skilled jobs after childbirth, again conditional on working at all. Results are available upon request.



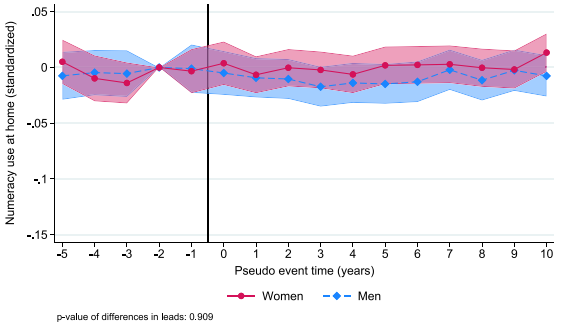
(a) Numeracy use at work



(b) Numeracy use at home



(c) Numeracy use at work (employed respondents)



(d) Numeracy use at home (employed respondents)

Fig. 10. Child penalties in numeracy use at work and in everyday life.
Notes: Figure plots the event-time coefficients α_j obtained from estimating equation (2), with matching controls, employed and unemployed separately. The dependent variables are numeracy use at work and at home. Shaded areas represent 95% confidence intervals. The corresponding summary estimates are shown in Appendix Table A.7.
Source: PIAAC international PUF.

4.3. Use of numeracy skills at work and at home

In this subsection, we analyse the use of numeracy skills to better understand the potential mechanisms behind the small immediate drop in skills for parents and why there is no larger drop for mothers despite their reduced employment following childbirth. As documented in Kleven et al. (2024a), having a child does not result in any worsening in labour market outcomes of fathers across a large number of countries. Hence, the decrease in labour market skills of fathers that we find cannot be caused by not being in employment or working fewer hours. Instead, if we assume skills to accumulate and depreciate based on their usage, a change in skill-use patterns could explain fathers' decline in measured cognitive performance.

The PIAAC dataset allows to analyse directly how skill use is affected by having children as the survey collects information on how often skill-related activities are performed.[37] Importantly, the questionnaire distinguishes between skills used at work and skills used at home. While numeracy use at work has a direct link to reduced employment, it is *a priori* unclear how numeracy use at home would be affected by having children.

Fig. 10 reports event study estimates for numeracy use at work and at home. Panel (a) shows that the use of numeracy skills at work mirrors the employment patterns documented in Fig. 4: mothers' numeracy use at work drops significantly and without recovery, while little is going on for fathers. However, if one restricts the sample to those in employment (panel c)—those not in employment mechanically have no numeracy use at work—we see no differences between mothers and fathers. In contrast, for numeracy use in everyday life we find a positive child penalty, i.e. mothers' skill use is increasing compared to that of fathers (panels b, d). Taken together, these results suggest that child penalties in numeracy skill use seem to be entirely driven by labour market participation and the lower numeracy use at work for mothers could be an explanation for their slightly larger drop in numeracy skills.

[37] The activities related to numeracy skills are: 'Calculate prices, costs or budgets'; 'Use or calculate fractions, decimals or percentages'; 'Use a calculator (hand held or computer-based)'; 'Prepare charts graphs or tables'; 'Use simple algebra or formulas'; 'Use advanced maths or statistics'.

4.4. Survey response behaviour

Having a child comes with many changes that could lead to a decrease in cognitive skills, regardless of labour market status. Specifically, parents tend to sleep less and with more interruptions, which has been linked to worse cognitive performance (Alhola and Polo-Kantola, 2007). While we do not observe sleeping behaviour in the PIAAC data, we provide evidence from Germany on this mechanism. The SOEP data, which we also use to validate the pseudo-panel approach in Section 3, contain a variable indicating respondents' satisfaction with their sleep. It ranges from 0 (completely dissatisfied) to 10 (completely satisfied) and has been part of the questionnaire since 2008. Appendix Figure A.11 shows the evolution of sleep satisfaction of German men and women around the birth of their first child.[38] There is a large decrease of satisfaction with sleep for both mothers and fathers after childbirth. This drop is more pronounced for women (up to 20 percent), starting from the year before childbirth, i.e. during pregnancy. Nonetheless, there is also a noteworthy decline in sleep satisfaction for fathers of around eight percent right after childbirth. For both parents, these effects do not entirely fade out after 10 years. Although this evidence can only be presented for Germany, it is likely to be a more universal result, as most parents would arguably attest, and suggests a decline in sleep quality for new parents that could in turn lead to worse cognitive functioning (Alhola and Polo-Kantola, 2007).[39]

In addition, performance in PIAAC may be driven by effort, which could be substantially different for parents of young children due to childcare responsibilities and other time commitments.[40] The PIAAC survey provides information on respondents' behaviour while answering the questionnaire which can be used to assess the channel of increased stress during the survey for parents. In particular, there is information on several behavioural dimensions on each skill question the respondent has answered. First, there is a variable indicating whether a question has been answered at all and whether the answer is correct.[41] From this information, we can calculate a share of non-responses for each participant as a proxy for skipping skill questions. Overall, leaving more numeracy questions unanswered is correlated with lower numeracy scores (not shown). Furthermore, there are records on how much time a participant has spent on each question. The average time spent on a question is generally positively associated with the numeracy score (not shown) as has also been documented in PISA tests (Anaya and Zamarro, 2024). Appendix Figure A.12 shows child penalties in these two behavioural measures for male and female parents. There is a slight increase of unanswered numeracy questions for both parents, especially for those who just experienced the birth of their fist child, but no gender differences. This speaks in favour of gender-independent skipping behaviour due to stress, tiredness or reduced effort. Instead, no clear pattern can be observed for the average time spent on each question.[42]

4.5. Components of numeracy scores

While the scores calculated and provided by PIAAC are a convenient and comparable measure of skills, their aggregate nature does not allow for a more detailed assessment of separate components based on question content. The plausible values we use in our main analysis are the result of a procedure following item response theory that the OECD performs to correct for imprecisions in the assessment of skills. This allows to provide scores even for respondents who have answered very few or none of the questions related to some skills. Additionally, actual answers of respondents are provided in the PIAAC dataset which allows us to look at different topics the questions refer to, e.g. work- and non-work-related questions.

To assess how comparable the actual responses and the composite scores are, we first re-estimate child penalties in numeracy skills using only actual responses of participants. To make this measure more similar to the scores used in the main analysis, we construct an average of the correct responses through weighting the questions by their respective item difficulty as described in PIAAC's technical report (OECD, 2016).[43] Appendix Figure A.13 shows the equivalent of Fig. 7 using the standardised difficulty-weighted share of correct answers among the questions each individual has actually responded to as a numeracy measure. Similarly to the composite score, we estimate that mothers' share of correct responses drops by around 0.15 standard deviations (equivalent to 4.6 pp or 6.7% of the sample mean) in the long-term. Using this measure, the drop for fathers is smaller such that a more distinct, yet still small, overall penalty arises. It is important to note, though, that these actual responses do not account for any imprecisions in measuring individual ability as the composite scores do.

While potentially not as accurate as the composite scores, using actual scores from individual questions allows for a deeper analysis of question types. More specifically, the questions related to numeracy can be divided into four so-called contexts: 'work-related', 'personal/everyday life','society and community', and 'education and training' (OECD, 2019). Given the importance of skills

[38] Thereby we extend the analysis from Richter et al. (2019) who study the sleep duration and satisfaction of parents using the same data but for a shorter time period.

[39] Using PIAAC data, we also explore whether other imperfect proxies for stress, i.e. job switching or working in multiple jobs, were affected by parenthood, but found no evidence supporting this.

[40] Another potential mechanism biasing our estimates could be that parents, especially those of young children, are less likely to participate in PIAAC. The survey aims to be representative within countries in a range of dimensions including age and gender (OECD, 2016), which are highly predictive of parental status. In Appendix Figure A.10, we report the share of parents by age and gender with expected patterns: the share of parents gradually increases, men become parents at older ages than women, and the share of parents with young children (under the age of 10) peaks in the 30 s. The smooth distributions give no indication that parents of (young) children are less likely to be part of the sample.

[41] Not all questions are answered by all participants so this variable could be missing because respondents were never presented a particular question. This would not be counted as non-response in our measure.

[42] We also document no differences for a measure of extreme response times, i.e. being below the 10th or above the 90th percentile of the average response time per question (not shown). This measure of extreme timing is on average negatively correlated with a respondent's numeracy score.

[43] Full details on how the scores are constructed are not published. Due to this, we are unable to calculate fully comparable scores based on actual responses.

related to the workplace for our analysis, Appendix Figure A.14 shows the child penalty in the standardised share of correct answers — again weighted by item difficulty — from work-related and non-work related contexts. As for the overall score, we identify that mothers answer around 0.09–0.11 standard deviations (5 pp) fewer questions correctly compared to fathers, and this does not seem to differ by the actual content of the questions being more or less related to work.

4.6. Cross-country differences

While the relatively small number of countries and of first-time parents in our data limits the statistical precision required to assess detailed cross-country variation, we present some analyses where we group countries along several dimensions of interest. Specifically, we focus on three gender- and family-related dimensions. First, we group countries depending on the size of child penalties in employment from Kleven et al. (2024a). Second, we look at child care availability, proxied by public spending on early childhood education and care and enrolment in child care at ages 0–2 and 3–5. Lastly, we make use of differences in gender norms across countries, measured by the share of respondents who expect a young child to suffer if their mother works for pay.

Appendix Table A.8 shows child penalties in numeracy scores in countries with above- and below-median child penalties in employment. We first re-estimate our main result in the reduced sample of countries with available data and show that it is similar in both direction and magnitude to the full sample (column 1). When performing the sample split along the median (columns 2 and 3), we see that countries with relatively *low* employment penalties are the ones that more strongly resemble our main results, although the difference between the two country groups is not statistically significant. These results suggest that countries with higher employment shares among (early) mothers are more likely to see gendered patterns of skill loss after childbirth. Intuitively, this could speak for skill loss being related to occupational characteristics rather than being employed at all. In addition, countries with lower child penalties in employment also have higher average numeracy scores for both men and women, hence there may be more scope for skill losses after childbirth in these countries.

Similarly, we present country splits by child care availability. We use three indicators from the OECD Family Database as proxies for the relevance of child care in the respective countries: public spending on childcare and early education (PF3.1) and child care enrolment at ages 0–2 and 3–5 (PF3.2).[44] We acknowledge though that these measures do not only capture child care availability but are also influenced by selection into child care and the effectiveness of public spending. For each country, we use the value reported in the respective PIAAC survey year or the closest available year. Appendix Table A.9 reports the results of re-estimating our main results for the reduced sample excluding countries with missing data and splitting the sample by the median of the child care measures. The main results in the reduced sample again very closely resemble our patterns from Table 2. While the estimates for gender differences in skill evolution after childbirth tend to be larger in countries with high child care utilisation and spending, none of the differences are statistically significant different from each other.

Lastly, we delve deeper into cross-country differences regarding gender norms from the joint European Values Study (EVS) and World Values Survey (WVS) 2017–2022. As a measure of gender roles, we use the answers to the question whether a (pre-school) child suffers if the mother works for pay.[45] Appendix Table A.10 reports the results of re-estimating the main result on all PIAAC countries that are part of the joint EVS/WVS as well as the median split according o gender norms. While the reduced sample with available gender norms does not show a clear child penalty in numeracy any more, this masks cross-country heterogeneity. In particular, countries with more liberal gender norms, i.e. less agreement to the above statement, show lower post-childbirth skills for mothers, while this is not the case for fathers. The difference is statistically different from zero. Although this may seem surprising, it is consistent with findings on employment patterns. Countries with more liberal gender norms have lower child penalties in employment (as in Kleven et al., 2024a) and higher numeracy scores on average. These two factors could imply that there is a larger scope for post-birth skill loss in these countries.

5. Concluding remarks

This paper investigates gender differences in the evolution of labour market skills around parenthood. We use data from the Survey of Adult Skills of the Programme for the International Assessment of Adult Competencies (PIAAC) and primarily focus on numeracy skills while also showing selected results for measures of literacy and problem solving. To estimate child penalties in labour market skills using this single cross-sectional dataset, we adapt the matching procedure developed by Kleven (2025). We validate our estimation of child penalties in a single cross-section using data on employment and wages from the German Socio-Economic Panel (SOEP), hereby using the dataset as a panel, a repeated cross-section and a single cross-section. Furthermore, we show that this approach also works for labour market outcomes in the PIAAC dataset. Then, we turn to estimating child penalties in skills for both mothers and fathers after the birth of their first child.

Our main results show that the estimation of child penalties in numeracy skills depends heavily on the inclusion of education levels as control variables, i.e. to tease out time trends/cohort differences in educational attainment and to potentially account for

[44] Indicators can be found here: https://www.oecd.org/en/data/datasets/oecd-family-database.html (last accessed on April 30, 2025). The spending indicator captures the total public expenditure on early childhood education and care, in per cent of GDP, 1980–2019/20. Enrolment is measured as the percent of children enrolled in early childhood education and care services (ISCED 0 and other registered ECEC services), 0- to 2-year-olds, 2005–2022, and the percent of children enrolled in early childhood education and care (ISCED 2011 level 0) or primary education (ISCED 2011 level 1), 3- to 5-year-olds, 2005–2021, respectively.

[45] See here: https://europeanvaluesstudy.eu/methodology-data-documentation/survey-2017/joint-evs-wvs/data-and-documentation-joint-evs-wvs/ (last accessed on April 30, 2025).

the latent ability component of numeracy skills. While there seem to be long-run child penalties in skills without accounting for differences in education, these become much smaller when including educational attainment. The absence of large child penalties in skills once we condition on cohort differences in education imply that the reduced career progression of mothers compared to fathers after the birth of their first child cannot be explained much by a loss of general labour market-relevant human capital such as numeracy competencies.

While we can exclude general skills used on the labour market as a main channel for existing child penalties in other labour market outcomes, we cannot rule out other skill-related mechanisms. For example, occupation- and firm-specific human capital might change faster during parenthood than general skills. If mothers change their job more often after parenthood than fathers (see e.g. Casarico and Lattanzio, 2023; Bang and Wang, 2024), they may lack the occupation- and firm-specific skills in their new firm relatively more. This in turn points at social norms determining preferences for certain jobs vs. others (e.g. in terms of flexibility) for mothers as an important channel of the established child penalties on the labour market.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2025.105245.

Data availability

Link to replication package (Zenodo): https://doi.org/10.5281/zenodo.17979296.

References

Ahammer, A., Glogowsky, U., Halla, M., Hener, T., 2023. The Parenthood Penalty in Mental Health: Evidence from Austria and Denmark. IZA Discussion Paper 16459.
Alhola, P., Polo-Kantola, P., 2007. Sleep deprivation: Impact on cognitive performance. Neuropsychiatr. Dis. Treat. 3 (5), 553–567.
Anaya, L.M., Zamarro, G., 2024. The role of student effort on performance in PISA: Revisiting the gender gap in achievement. Oxf. Econ. Pap. 76 (2), 533–560.
Andresen, M.E., Nix, E., 2022. What causes the child penalty? Evidence from adopting and same-sex couples. J. Labor Econ. 40 (4), 971–1004.
Baertsch, L., Sandner, M., 2025. Reducing the child penalty by incentivizing maternal part-time work? Labour Econ. 95, 102759.
Bahar, E., Bradshaw, N., Deutscher, N., Montaigne, M., 2025. Children and the gender earnings gap: evidence for Australia. Econ. Rec. 101 (332), 41–75.
Bandiera, O., Kotia, A., Lindenlaub, I., Moser, C., Prat, A., 2024. Meritocracy across Countries. NBER Working Paper 32375.
Bang, M., Wang, H., 2024. Job search and mobility over the life cycle: Implications for the child penalty. Mimeo.
Barschkett, M., Bosque-Mercader, L., 2023. Building Health across Generations: Unraveling the Impact of Early Childcare on Maternal Health. DIW Berlin Discussion Paper 2059.
Battisti, M., Fedorets, A., Kinne, L., 2023. Cognitive Skills among Adults: An Impeding Factor for Gender Convergence? IZA Discussion Paper No. 16134.
Becker, G.S., Hubbard, W.H., Murphy, K.M., 2010. Explaining the worldwide boom in higher education of women. J. Hum. Cap. 4 (3), 203–241.
Berniell, I., Berniell, L., De la Mata, D., Edo, M., Marchionni, M., 2021. Gender gaps in labor informality: The motherhood effect. J. Dev. Econ. 150, 102599.
Bertrand, M., Goldin, C., Katz, L.F., 2010. Dynamics of the gender gap for Young professionals in the financial and corporate sectors. Am. Econ. J.: Appl. Econ. 2 (3), 228–255.
Bertrand, M., Kamenica, E., Pan, J., 2015. Gender identity and relative income within households. Q. J. Econ. 130 (2), 571–614.
Blundell, R., Costa Dias, M., Meghir, C., Shaw, J., 2016. Female labor supply, human capital, and welfare reform. Econometrica 84 (5), 1705–1753.
Burdett, K., Carrillo-Tudela, C., Coles, M., 2020. The cost of job loss. Rev. Econ. Stud. 87 (4), 1757–1798.
Casarico, A., Lattanzio, S., 2023. Behind the child penalty: understanding what contributes to the labour market costs of motherhood. J. Popul. Econ. 1–23.
Charles, K.K., Luoh, M.-C., 2003. Gender differences in completed schooling. Rev. Econ. Stat. 85 (3), 559–577.
Christl, M., Köppl-Turyna, M., 2020. Gender wage gap and the role of skills and tasks: evidence from the Austrian PIAAC data set. Appl. Econ. 52 (2), 113–134.
Ciasullo, L., Uccioli, M., 2024. What Works for Working Couples? Work Arrangements, Maternal Labor Supply, and the Division of Home Production. IZA Discussion Paper 16991.
Cohen, J., Johnston, A.C., Lindner, A., 2025. Skill depreciation during unemployment: Evidence from panel data. Am. Econ. J.: Appl. Econ. 17 (3), 208–235.
Cortés, P., Pan, J., 2023. Children and the remaining gender gaps in the labor market. J. Econ. Lit. 61 (4), 1359–1409.
De Quinto, A., Hospido, L., Sanz, C., 2021. The child penalty: evidence from Spain. SERIEs 12, 585–606.
Dinerstein, M., Megalokonomou, R., Yannelis, C., 2022. Human capital depreciation and returns to experience. Am. Econ. Rev. 112 (11), 3725–3762.
Drummond, S., Brown, G.G., 2001. The effects of total sleep deprivation on cerebral responses to cognitive performance. Neuropsychopharmacology 25, S68–S73.
Edin, P.-A., Gustavsson, M., 2008. Time out of work and skill depreciation. ILR Rev. 61 (2), 163–180.
Erosa, A., Fuster, L., Kambourov, G., Rogerson, R., 2022. Hours, occupations, and gender differences in labor market outcomes. Am. Econ. J.: Macroecon. 14 (3), 543–590.
Eurostat, 2020. Population by educational attainment level, sex and age (%): main indicators. Eurostat. Luxemb..
Falck, O., Heimisch-Roecker, A., Wiederhold, S., 2021. Returns to ICT skills. Res. Policy 50 (7), 104064.
Gallen, Y., 2024. Motherhood and the gender productivity gap. J. Eur. Econ. Assoc. 22 (3), 1055–1096.
Glogowsky, U., Hansen, E., Sachs, D., Lüthen, H., 2025. The evolution of child-related gender inequality in Germany and the role of family policies, 1960–2018. Eur. Econ. Rev. 175, 105018.
Goebel, J., Grabka, M.M., Liebig, S., Kroh, M., Richter, D., Schröder, C., Schupp, J., 2019. The German socio-economic panel (SOEP). Jahrbücher Natl. Stat. 239 (2), 345–360.
Goldin, C., 2014. A grand gender convergence: Its last chapter. Am. Econ. Rev. 104 (4), 1091–1119.
Goldin, C., 2024. Nobel lecture: An evolving economic force. Am. Econ. Rev. 114 (6), 1515–1539.

Goldin, C., Mitchell, J., 2017. The new life cycle of women's employment: Disappearing humps, sagging middles, expanding tops. J. Econ. Perspect. 31 (1), 161–182.
Hanushek, E.A., 1986. The economics of schooling: Production and efficiency in public schools. J. Econ. Lit. 24 (3), 1141–1177.
Hanushek, E.A., Kinne, L., Witthöft, F., Woessmann, L., 2025. Age and cognitive skills: Use it or lose it. Sci. Adv. 11 (10), eads1560.
Hanushek, E.A., Schwerdt, G., Wiederhold, S., Woessmann, L., 2015. Returns to skills around the world: Evidence from PIAAC. Eur. Econ. Rev. 73, 103–130.
Heckl, P., Wurm, E., 2024. Workplace Breastfeeding and Maternal Employment. CESifo Working Paper 11248.
Huttunen, K., Troccoli, C., 2023. Evolution of the child penalty. Mimeo.
Jackson, P., Ortego-Marti, V., 2024. Skill loss during unemployment and the scarring effects of the COVID-19 pandemic. Labour Econ. 88, 102516.
Jensen, M.F.l., 2024. Gender differences in returns to skills: Evidence from matched Vacancy-Employer-Employee data. Mimeo.
Jessen, J., 2022. Culture, children and couple gender inequality. Eur. Econ. Rev. 104310.
Jewsbury, P.A., Jia, Y., Gonzalez, E.J., 2024. Considerations for the use of plausible values in large-scale assessments. Large-Scale Assess. Educ. 12, 24.
Karademir, S., Laliberté, J.-W.P., Staubli, S., 2024. The Multigenerational Impact of Children and Childcare Policies. NBER Working Paper 32204.
Khorramdel, L., von Davier, M., Gonzalez, E., Yamamoto, K., 2020. Plausible values: Principles of item response theory and multiple imputations. Large-Scale Assessments in Education: Issues and Methodologies. Springer, Cham.
Kim, A., Hahn, Y., 2022. The motherhood effect on labour market outcomes: evidence from South Korea. Asian-Pac. Econ. Lit. 36 (2), 71–88.
Kleven, H., 2025. The Geography of Child Penalties and Gender Norms: Evidence from the United States. NBER Working Paper 30176.
Kleven, H., Landais, C., 2017. Gender inequality and economic development: fertility, education and norms. Economica 84 (334), 180–209.
Kleven, H., Landais, C., Leite-Mariante, G., 2024a. The child penalty atlas. Rev. Econ. Stud.: Rdae104.
Kleven, H., Landais, C., Posch, J., Steinhauer, A., Zweimüller, J., 2019a. Child penalties across countries: Evidence and explanations. In: AEA Papers and Proceedings. Vol. 109, pp. 122–126.
Kleven, H., Landais, C., Posch, J., Steinhauer, A., Zweimüller, J., 2024b. Do family policies reduce gender inequality? Evidence from 60 years of policy experimentation. Am. Econ. J.: Econ. Policy 16 (2), 110–149.
Kleven, H., Landais, C., Søgaard, J.E., 2019b. Children and gender inequality: Evidence from Denmark. Am. Econ. J.: Appl. Econ. 11 (4), 181–209.
Kleven, H., Landais, C., Søgaard, J.E., 2021. Does biology drive child penalties? evidence from biological and adoptive families. Am. Econ. Rev.: Insights 3 (2), 183–198.
Kuka, E., Shenhav, N., 2024. Long-Run effects of incentivizing work after childbirth. Am. Econ. Rev. 114 (6), 1692–1722.
Lalé, E., 2018. Loss of skill and labor market fluctuations. Labour Econ. 50 (C), 20–31.
Laun, T., Wallenius, J., 2021. Having It All? Employment, Earnings, and Children. Scand. J. Econ. 123 (1), 353–381.
Lebedinski, L., Perugini, C., Vladisavljević, M., 2023. Child penalty in Russia: evidence from an event study. Rev. Econ. Househ. 21 (1), 173–215.
Lemoine, A., Spitzer, S., Reiter, C., 2025. Parenting leave duration and mothers' skills along the life course. Mimeo.
Lim, N., Duletzki, L.-M., 2023. The Effects of Public Childcare Expansion on Child Penalties: Evidence from West Germany. Boston University-Department of Economics.
Low, H., Sánchez-Marcos, V., 2015. Female labour market outcomes and the impact of maternity leave policies. IZA J. Labor Econ. 4, 1–22.
Meng, L., Zhang, Y., Zou, B., 2023. The motherhood penalty in China: Magnitudes, trends, and the role of grandparenting. J. Comp. Econ. 51 (1), 105–132.
Minkel, J.D., Banks, S., Htaik, O., Moreta, M.C., Jones, C.W., McGlinchey, E., Simpson, N.S., Dinges, D., 2012. Sleep deprivation and stressors: evidence for elevated negative affect in response to mild stressors when sleep deprived. Emotion 12 5, 1015–1020.
Mitchell, M.B., Cimino, C.R., Benitez, A., Brown, C.L., Gibbons, L.E., Kennison, R., Shirk, S.D., Atri, A., Robitaille, A., MacDonald, S.W.S., Lindwall, M., Zelinski, E., Willis, S.L., Schaie, K., Johansson, B., Dixon, R.A., Mungas, D., Hofer, S., Piccinin, A., 2012. Cognitively stimulating activities: Effects on cognition across four studies with up to 21 years of longitudinal data. J. Aging Res. 2012.
OECD, 2013. Technical Report of the Survey of Adult Skills (PIAAC). VOCEDplus, The International Tertiary Education and Research Database.
OECD, 2016. Technical Report of the Survey of Adult Skills (PIAAC) (2nd Edition). Technical Report.
OECD, 2019. The Survey of Adult Skills: Reader's Companion. Organisation for Economic Co-Operation and Development.
Ortego-Marti, V., 2017. Differences in skill loss during unemployment across industries and occupations. Econom. Lett. 161, 31–33.
Parfitt, Y., Ayers, S., 2014. Transition to parenthood and mental health in first-time parents. Infant Ment. Health J. 35 3, 263–273.
Perry, A., Wiederhold, S., Ackermann-Piek, D., 2014. How can skill mismatch be measured? New approaches with PIAAC. Methods Data Anal. 8 (2), 38.
Pertold-Gebicka, B., Pertold, F., Gupta, N.D., 2016. Employment adjustments around childbirth. Eur. Econ.: Labor Soc. Cond. EJournal.
Pető, R., Reizer, B., 2021. Gender differences in the skill content of jobs. J. Popul. Econ. 34 (3), 825–864.
Pilcher, J., Huffcutt, A.I., 1996. Effects of sleep deprivation on performance: a meta-analysis. Sleep 19 4, 318–326.
Rebollo-Sanz, Y.F., De la Rica, S., 2022. Gender gaps in skills and labor market outcomes: evidence from the PIAAC. Rev. Econ. Househ. 20 (2), 333–371.
Reiter, C., Spitzer, S., 2025. When gender trumps skills: Employment trajectories of Austrian parents after their first birth. Mimeo.
Richter, D., Krämer, M.D., Tang, N.K., Montgomery-Downs, H.E., Lemola, S., 2019. Long-term effects of pregnancy and childbirth on sleep satisfaction and duration of first-time and experienced mothers and fathers. Sleep 42 (4), zsz015.
Sieppi, A., Pehkonen, J., 2019. Parenthood and gender inequality: Population-based evidence on the child penalty in Finland. Econom. Lett. 182, 5–9.
Sundberg, A., 2024. The Child Penalty in Sweden: Evidence, Trends, and Child Gender. Tech. Rep., IFAU-Institute for Evaluation of Labour Market and Education Policy.
Woessmann, L., 2016. The importance of school systems: Evidence from international differences in student achievement. J. Econ. Perspect. 30 (3), 3–32.