Child Penalties in Labour Market Skills*

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Abstract

Child penalties in labour market outcomes are well-documented: after childbirth, mothers' employment and earnings drop persistently compared to fathers. Beyond gender norms, a potential driver could be the loss in labour market skills due to mothers' longer employment interruptions. This paper estimates child penalties in adult cognitive skills by adapting the pseudo-panel approach to a single cross-section of 29 countries in the PIAAC dataset. We find a persistent drop in numeracy skills after childbirth for both parents between 0.13 (short-run) and 0.16 standard deviations (long-run), but no statistically significant difference between mothers and fathers. Estimates of child penalties in skills strongly depend on controlling for pre-determined characteristics, especially education. Additionally, there is no evidence for worse occupational skill matches for mothers after childbirth. Our findings suggest that changes in general labour market skills cannot explain child penalties in labour market outcomes, and that a cross-sectional estimation of child penalties can be sensitive to characteristics of the outcome variable.

JEL: *I20, J13, J16, J24*
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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 recently received a lot of attention in the literature, and has emerged as the main explanation for remaining gender gaps in labour market outcomes in most high-income countries (Cortés and Pan, 2023; Kleven, 2023; Kleven et al., 2024a, 2019a,b). 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, it has not been studied 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 that individuals use on the labour market 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 evolve 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 by Kleven (2023) 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 such data, they show that child penalties obtained using the matching procedure closely mimic those estimated with panel data. We adapt their procedure to a single cross-section in a cross-country setup, and apply it to data from the Programme for the International Assessment of Adult Competencies (PIAAC), which includes labour market skills in different domains for individuals aged 16 to 65. 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 group of countries.

We find that numeracy skills drop in early parenthood for both parents by around 13 percent of a

[1] 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. Nonetheless, we acknowledge that this expression is not ideal from a normative point of view.

[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).

standard deviation. This corresponds to around one quarter of the difference in average numeracy skills between those with upper or post-secondary education and those with tertiary education. Once we control for pre-determined characteristics and in particular education, short- and long-run estimates for mothers and fathers are statistically indistinguishable. This means that the development of skills after childbirth does not mirror the gender differences in other labour market outcomes around parenthood where mothers are typically more affected than fathers.[3] Using returns to labour market skills as measured in PIAAC (Hanushek et al., 2015)—which we confirm using our estimation sample—, these lower numeracy skills would translate into around 3% lower wages for both parents. Child penalties in literacy and problem-solving skills exhibit similar patterns, with somewhat larger drops for both mothers and fathers, but again we see no gender 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 do not observe differential skill depreciation 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.[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 associated with an at best modest shift from *perfect* to *good* 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. In contrast, we can reject that parenthood leads to more *poor* skill matches for mothers where occupational skill demands are strongly misaligned with their skills.

Additionally, we look at outcomes related to numeracy levels 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*. Looking at raw answers to numeracy questions instead of PIAAC's derived numeracy score, weakly suggests a small child penalty in the share of correctly answered questions,

[3] If education is not included as a control, we estimate a long-term child penalty of 0.17 sd. 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 (Erosa et al., 2022; Goldin, 2014; Kleven et al., 2019b; Pertold-Gebicka et al., 2016; Pető and Reizer, 2021).

[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.

driven both by work- and non-work related assessment questions.

To assess the somewhat surprising 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).[6] In turn, high levels of stress and reduced sleep can impair cognitive functioning and decision-making, including memory, attention, and executive functions, which are crucial for numeracy skills (Drummond and Brown, 2001; Minkel et al., 2012; Pilcher and Huffcutt, 1996). We can 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, and 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 longer (or much shorter) to complete the survey.

Our results show that drops in general labour market skills (and associated lower labour market returns) for mothers are unlikely to play a key role in the observed child penalties in employment and wages. Instead, the findings are consistent with the view that all or most of the child penalties in employment and wages are driven by gender norms and expectations around gender differences in labour supply after childbirth and child care responsibilities. This implies that general training opportunities are not expected to counteract child penalties in labour market outcomes. A more promising avenue might be to increase the availability and accessibility of family-friendly firm and childcare policies.[7] These could mitigate the overall loss of labour market experience and firm-specific tenure as well as human capital accumulation that have all been shown to be associated with higher earnings (Burdett et al., 2020).[8] 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 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.[9]

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

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

[8]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 child-care 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 skill depreciation (Edin and Gustavsson, 2008; Low and Sánchez-Marcos, 2015).

[9]See OECD (2013), Chapter 3, for a small overview of the related literature in cognitive and neuropsychology. Additionally, Hanushek et al. (2024) find evidence of usage-related skill evolution using the small panel extension from PIAAC in Germany. Unfortunately, there is not enough new parents in this panel dataset to systematically assess child penalties in a longitudinal framework.

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 that 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. While a relatively young literature, over the last years many empirical papers have measured child penalties in labour market outcomes across many countries (Kleven et al., 2024a).[10] Child penalties have been shown to be closely linked to societal norms as well as biological factors. 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.[11] 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 e.g. 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 (2023) 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 discussion on the causes and consequences of skill depreciation on the labour market. 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. (2023) 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.[12] However, there are clear differences between

[10] 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. (2023) 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), Bönke et al. (2023), 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.

[11] Similar evidence can be found in Jessen (2022) for cultural differences between East and West Germany and in Kleven (2023) for the United States.

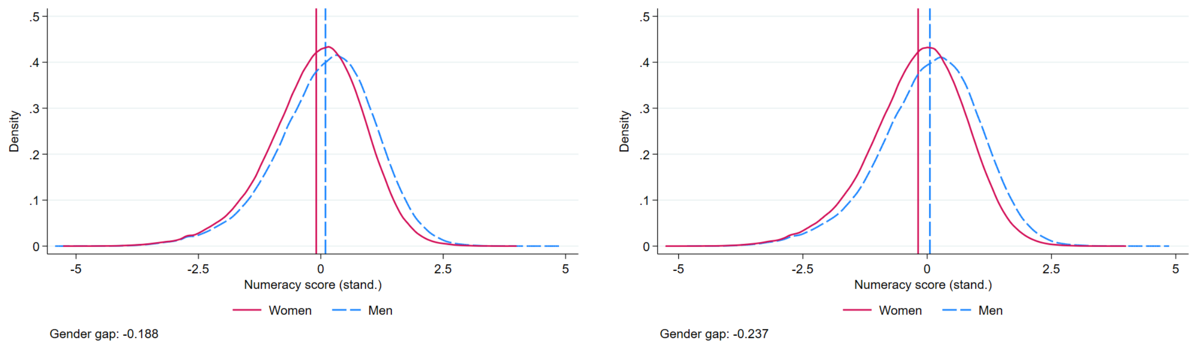
[12] Other related papers include Ortego-Marti (2017), who use PSID data to document differences in skill depreciation

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 potential skill depreciation as a consequence of having children. 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.

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.[13] PIAAC provides standardised measures of skills for individuals aged 16-65 in numeracy, literacy, and problem-solving,[14] 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. For each domain, skills are measured on a 500-point scale which is composed of individual scores from separate questions. We standardise the skill measures to have mean zero and standard deviation one within each country.[15] 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).

Figure 1: Distribution of numeracy scores by gender



(a) All (b) Parents

Notes: Panel (a) contains all respondents ($N = 171,778$) and panel (b) restricts the sample to parents ($N = 108,014$). Source: PIAAC international PUF.

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).

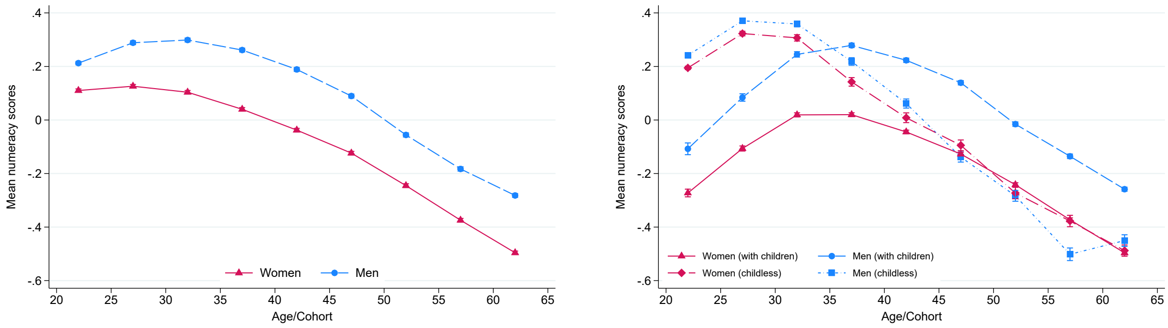
[13]The second wave of PIAAC was collected in 2022-2023 and is set to be released in December 2024. The full list of participating countries and the survey schedule can be found at https://www.oecd.org/skills/piaac/.

[14]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/skills/piaac/samplequestionsandquestionnaire.htm

[15]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 B.1).

Figure 1 shows 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 0.18 standard deviations (sd) for all respondents, and 0.23 standard deviations among parents. Hence, gender gaps in numeracy scores are pervasive and seem to be especially pronounced for parents.

Figure 2: Numeracy scores by age, gender, and parental status



(a) Numeracy scores by age and gender

(b) Numeracy scores by 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. Standardisation by country uses individuals' sampling probability. Source: PIAAC international PUF

Figure 2 shows average numeracy skills of men and women in 5-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 in terms of skills into parenthood 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 studying children as the potential motivation behind the gender skill gap. 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 shows average numeracy scores and ages at first childbirth by gender for the 29 countries that we use in our analysis.[16] 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.

[16] As described in section 3, we use 29 of the 35 surveyed countries 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

Country	Average numeracy score men	Average numeracy score women	Average age at first child-birth (men)	Average age at first child-birth (women)
Belgium	288	272	28	26
Chile	217	196	25	23
Czech Republic	280	271	26	23
Denmark	284	273	28	26
Ecuador	190	181	25	22
Estonia	276	270	25	23
Finland	288	278	28	26
France	260	249	28	25
Greece	256	249	30	25
Hungary	274	271	27	24
Ireland	262	250	28	26
Israel	257	246	28	25
Italy	252	242	30	26
Japan	294	282	30	27
Kazakhstan	247	247	26	24
Korea	269	258	29	26
Lithuania	268	266	26	24
Mexico	216	206	25	23
Netherlands	289	272	30	27
New Zealand	278	265	28	26
Norway	286	271	28	25
Peru	187	172	26	22
Poland	261	259	27	24
Singapore	265	251	30	27
Slovak Republic	277	275	26	23
Slovenia	260	255	27	24
Spain	252	240	29	26
Sweden	286	272	28	26
United Kingdom	269	254	28	25
Total: 29	262	251	27	25

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. Source: PIAAC international PUF

In order to estimate child penalties in cross-sectional data we generate a pseudo-panel of the outcomes of interest for parents, following Kleven (2023). 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 (2023) 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 B.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.[17] Kleven (2023) 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 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 B.1 shows the number of first-time parents we observe in each country, split by gender.[18] 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. Given the relatively small number of first-time parents for each country, we focus on the aggregate sample using all available observations and abstract from any country differences.

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 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 (2023), and iii) a single cross-section (see section 3).

3 Empirical Approach and Validation

We follow Kleven (2023) 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

[17] 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.

[18] The number of first-time parents we manage to match (1,079) is only slightly smaller than the total number of first-time parents in the full international PIAAC sample (1,193) and similarly distributed among the countries, which means that we can exclude large sample selection bias from matching.

year ($\mathbb{I}[y = s]$) dummies are included to partial out life-cycle effects and general time trends 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:[19]

$$y^g_{ist} = \sum_{j \neq -2} \alpha^g_j \cdot \mathbb{I}[j = t] + \sum_k \beta^g_k \cdot \mathbb{I}[k = age_{is}] + \sum_y \gamma^g_y \cdot \mathbb{I}[y = s] + \epsilon^g_{ist} \tag{1}$$

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 (2023) 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 likely to become parents in the upcoming years based on their characteristics. Besides gender, we match on educational attainment, being born in Germany, living in East or West Germany, cohabitation status, age, and survey year.[20] 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 $\sum_y \gamma^g_y \cdot [y = s]$, the term associated with the year dummies in equation (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.

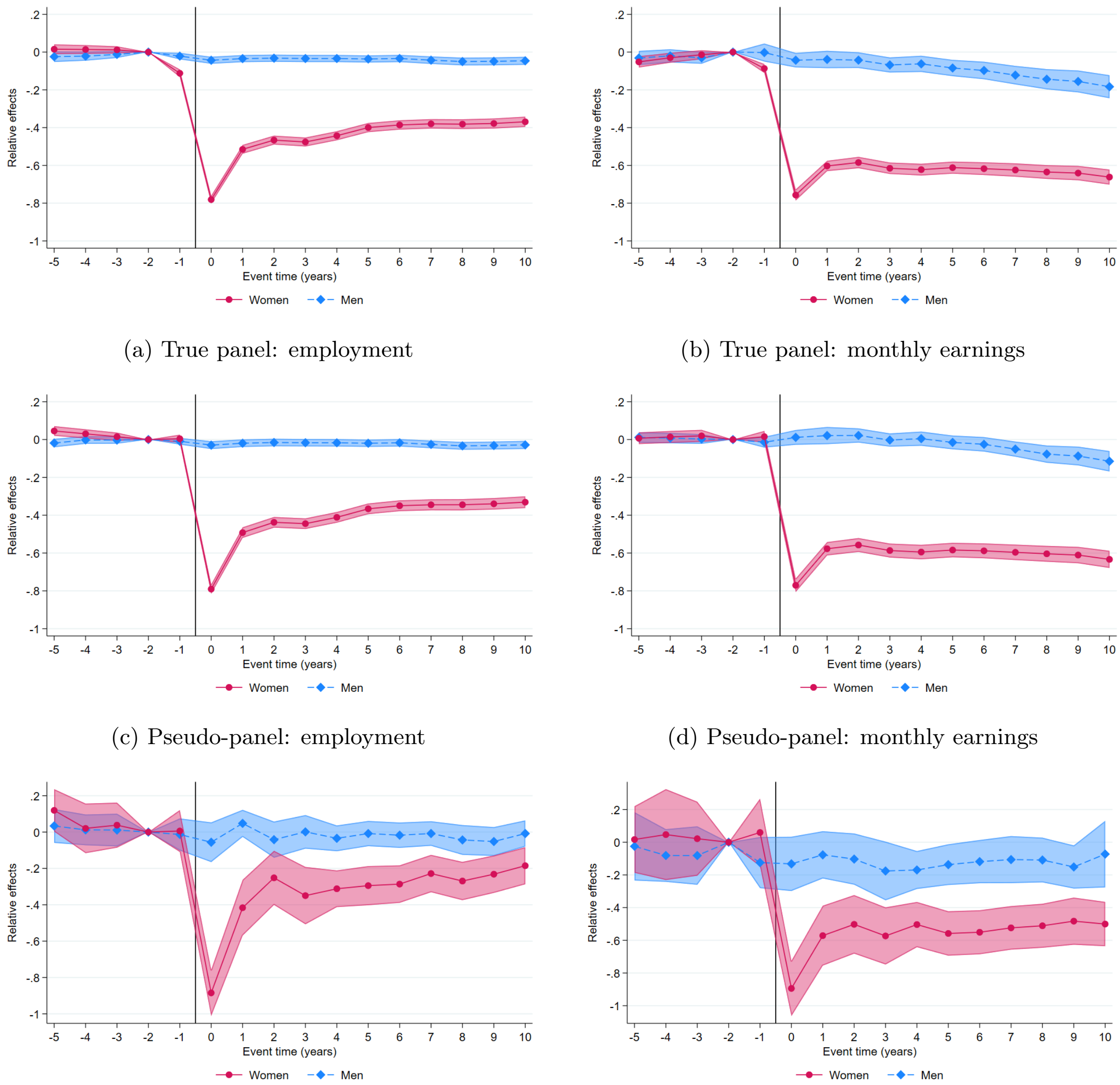
In Figure 3, we plot the α_j event-time coefficients from estimating equation (1) for employment and monthly earnings, using the three different procedures described above. The upper row shows coefficients for the true panel, the middle row for the pseudo-panel, and the bottom row for estimates based on a single cross-section.[21] 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 sample size drops dramatically when using only one survey year. Nevertheless, the patterns look reassuringly similar, and unambiguously document a child penalty for mothers in both employment and monthly earnings and little to no difference for fathers.

[19] 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.

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

[21] 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.

Figure 3: Child penalties in labour market outcomes—SOEP validation



(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

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 based on a pseudo-panel where the pre-birth observations are based on 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

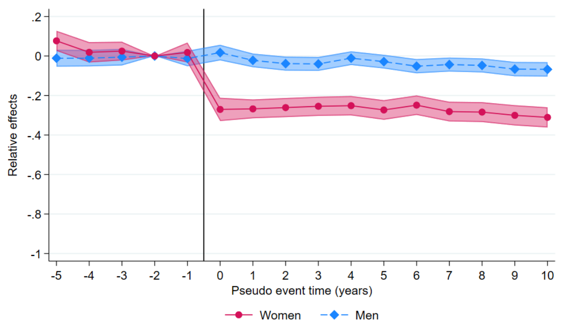
Single cross-section using PIAAC After showing how the estimation of child penalties in a panel can be adapted to a single cross-section, we now proceed to our estimation of interest, i.e. child penalties in numeracy skills from PIAAC. The matching procedure is slightly different due to the availability 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 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.[22] Instead of race, as used by Kleven (2023), we use a dummy for whether a respondent was born in the country they currently live in, and instead of U.S. states (Kleven, 2023) 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 B.1) from 29 countries to potentially multiple surrogate observations from younger childless individuals.[23]

Our slightly adapted estimation equation is then:

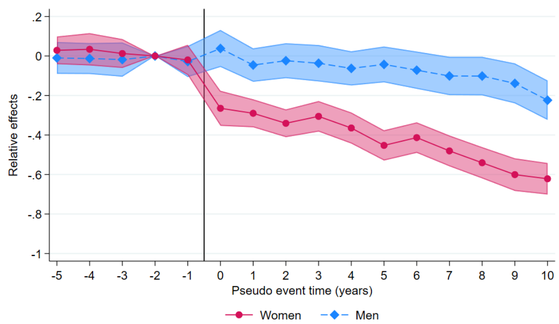
$$Y_{itc}^{g} = \sum_{j \neq -2} \alpha_j^g \, \mathbb{I}[j = t] + \sum_{k} \beta_k^g \, \mathbb{I}[k = age_i] + \mu_c + \nu_{itc}^{g} \tag{2}$$

where Y_{itc}^{g} measures our outcome (employment, earnings, skills) of individual i of gender g at event time t in country c. The α_j^g 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_k^g capture the influence of age, and we add country dummies μ_c to focus on within-country comparisons. 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. 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.[24] The event-time coefficients are statistically identified due to variation in age at first birth across individuals and across countries.

Figure 4: Child penalties in labour market outcomes—PIAAC validation



(a) Employment



(b) Monthly earnings

Notes: Plots show the event-time coefficients α_j obtained from estimating equation (2). Sample in panel (a) consists of all countries listed in Appendix Table B.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

Figure 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

[22]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.

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

[24]Using the German panel extension of PIAAC ('PIAAC-L'), Hanushek et al. (2024) show that skill evolution is indeed strongly related to age progression, in particular depending on the usage of skills on the job.

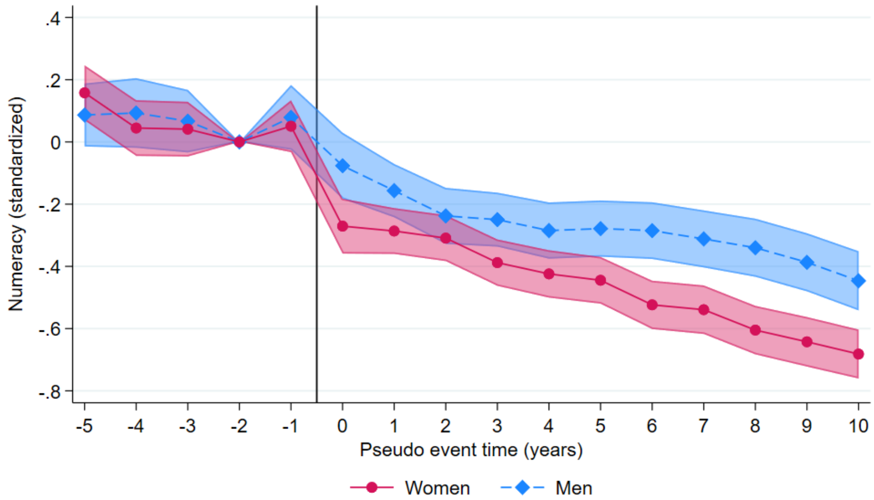
of women right after the birth event.[25]

4 Main Results

4.1 Parenthood and Labour Market Skills

Figure 5 plots the gender-specific event-time dummies α_j^g based on equation (2) using numeracy skills as our outcome. The dependent variable is the standardised score such that coefficient sizes 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 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 presented in Figures 3 and 4 and found in the previous literature, fatherhood seems to be associated with a significant reduction in numeracy skills.

Figure 5: Child penalties in numeracy scores

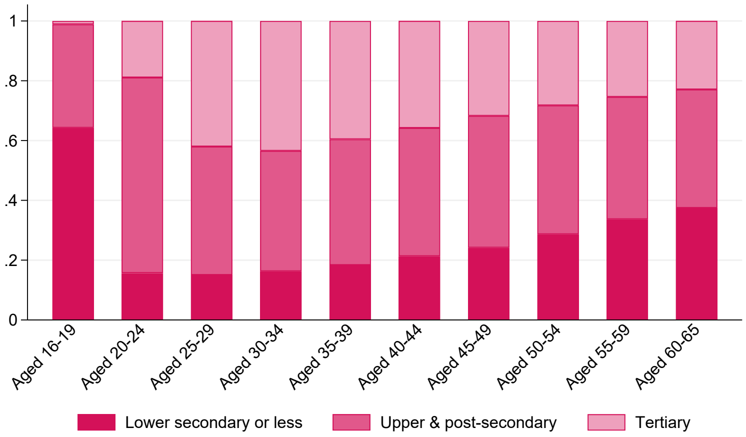


Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2). The dependent variable is the standardised numeracy score. Shaded areas represent 95% confidence intervals. The corresponding summary estimates are shown in Table B.4. Source: PIAAC international PUF

The overall decreasing pattern of numeracy skills after childbirth for both mothers and fathers raises the concern whether we might be picking up 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 in most high-income countries more likely to hold college degrees than men (Goldin, 2024; Kleven and Landais, 2017). Appendix Table B.2 shows that even though our estimation dataset contains a relatively wide range of ages for each event time, overall respondents in later event times naturally tend to be older which implies

[25] 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.

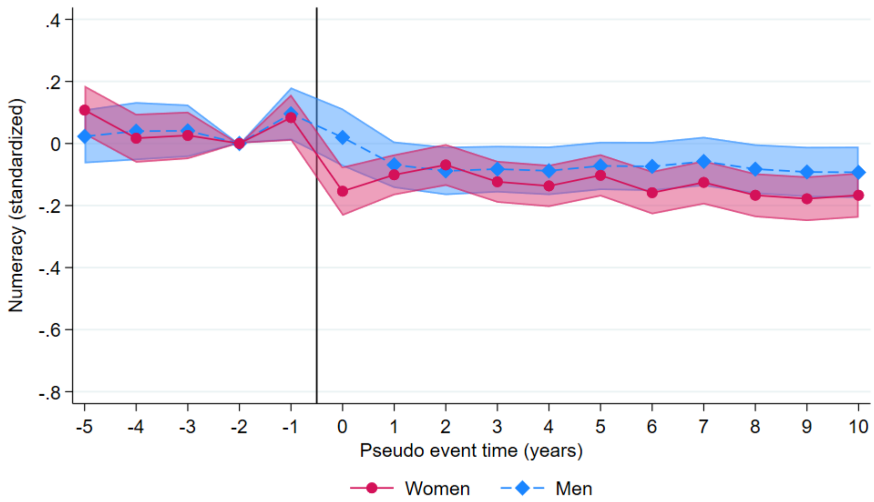
Figure 6: Differences in education levels between PIAAC cohorts



Notes: Figure shows education levels by age groups of all PIAAC respondents. Source: PIAAC international PUF

that on average the later event times contain individuals from earlier cohorts. Figure 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 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.[26]

Figure 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 country, and education levels. The dependent variable is the standardised numeracy score. Shaded areas represent 95% confidence intervals. Source: PIAAC international PUF

Consistent with this view, Figure 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.[27]

[26]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.

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

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. But most importantly, we do not observe diverging trends for mothers and fathers any more up to ten years after the birth of their first child. Instead, there is a similar drop for both parents after childbirth, and no evidence of a subsequent recovery. This is confirmed by estimates in Table 2. The short-term skill reduction for mothers and fathers is around 0.13 sd, but there is no significant difference in the estimate between mothers and fathers. The point estimate and standard errors allow us to rule out that the long-term coefficient is more than 0.1 sd larger for mothers, which following Hanushek et al. (2015) would correspond to wage differences of 1.8%.[28] While we believe that 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.

Table 2: Summary estimates for child penalties in numeracy (with matching controls)

	Men (1)	Women (2)	Women-Men (3)
Pre-birth	-0.0137	0.0047	0.0184
	(0.0290)	(0.0252)	(0.0384)
Short-term effect	-0.1175***	-0.1515***	-0.0340
	(0.0254)	(0.0217)	(0.0334)
Long-term effect	-0.1204***	-0.1851***	-0.0647*
	(0.0270)	(0.0234)	(0.0357)
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 Figure 7. The omitted category is two years before birth. Source: PIAAC international PUF

Child penalties estimated 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 Figure 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.[29] Hence, it seems that general trends in education affect skill levels much more than wage levels or other labour market outcomes.

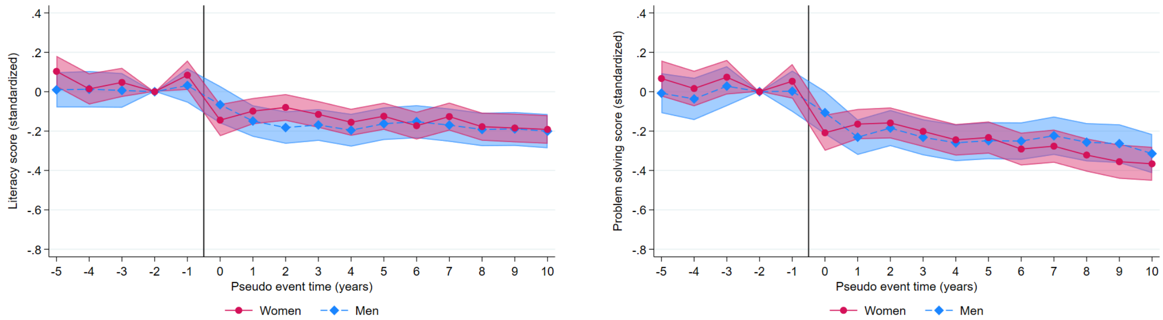
Figure 8 presents results for literacy and problem-solving skills, including the matching controls as in our preferred specification. As expected, due to the strong correlation of the different skill measures (see Appendix Figure A.6), the coefficients for literacy and problem-solving scores reveal very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

[28] 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, we identify for our sample of (becoming) parents average returns of 16 percent for women and men. As estimate of returns to skills are lower, using these numbers an even lower share of wage differences could be accounted for by skill differences induced by parenthood. We find no evidence for differential returns by pseudo-event time.

[29] 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.

patterns: no pre-birth differences, a drop for both parents right after childbirth, and no gap between mothers and fathers in the long run. The long-term estimates of around 0.2 sd for literacy and up to 0.3 sd for problem solving are shown in Appendix Table B.5. The long-term estimate on problem-solving is significantly larger for women compared to the other two outcomes, but also not statistically different to the drop for fathers.

Figure 8: Child penalties in literacy and problem-solving scores (with matching controls)



(a) Literacy score

(b) Problem-solving score

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 score. Shaded areas represent 95% confidence intervals. Source: PIAAC international PUF

Investigating possible sources of heterogeneity can inform the analysis of the relevant factors at work. First, we examine regional variation. Due to limited sample sizes per country, estimates at this level lack precision to draw meaningful conclusions, so we restrict the comparison to European countries (constituting the largest group with 19/29 countries) vs. non-European countries. Estimates plotted in Appendix Figure A.7 document no child penalties in numeracy skills in Europe as in the full sample and if anything a reverse (or negative) penalty in non-European countries, even if imprecisely estimated.

In Appendix Figure A.8, we split the sample by *current* employment status. Again, for the employed we observe the pattern described in the full sample where no child penalties in numeracy skills are visible. In the sample of unemployed respondents, there is some evidence for a reversed child penalty, albeit estimates are imprecise due to small sample sizes.

4.2 Implications for Skill (Mis-)match

Even though all previous analyses have shown no differential skill development for mothers and fathers, we may still be concerned about post-childbirth selection of parents into jobs that do not correspond (well) to their skillset. 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.

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 difficulty, they calculate country-specific numeracy (and literacy) skill requirements for each occupation. Appendix Figure A.9 shows average numeracy skill requirements by 1-digit ISCO occupations (the analysis uses 2-digit occupations) with broadly expected patterns: managers and professionals have the highest skill requirements, machine operators and elementary occupations the lowest. The figure also reports the average numeracy scores of workers in those occupations: with two exceptions (skilled agricultural workers and the armed forces), the average numeracy score is decreasing almost monotonically with lower skills requirements.

Occupations are subsequently mapped to quintiles of skill requirements and similarly PIAAC respondents are assigned to quintiles based on their numeracy scores. Skill mismatch is then defined as the distance between the numeracy score quintile and the skill requirement quintile of the current occupation.[30] 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 distance is at most one quintile, and 'poor' for distances larger than one quintile. A continuous measure using the Euclidian distance between individual skill use and job skill requirements complements their analysis. Appendix Figure A.10 shows that on average skill (mis-)match between 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 (2.6 percentage points or 10% more perfect matches, statistically significant at the 1% level).

Figure 9 plots the α_j coefficients of equation (2) for these four measures of skill mismatch, summary coefficients are reported in Appendix Table B.6. We see suggestive evidence for a small reduction in perfect matches for mothers (significant at the 10% level) and a compensating increase in good matches. Poor matches and a cardinal measure of distance are not affected. Hence, a mismatch in skill use 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.

5 Additional Results

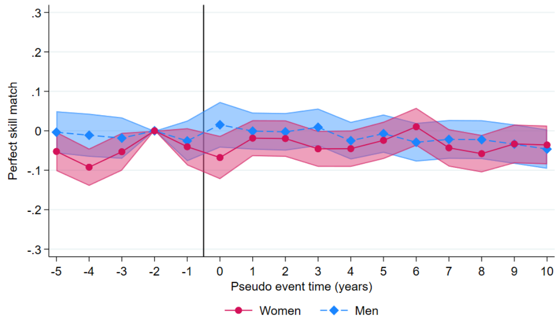
5.1 Use of Numeracy Skills at Work and at Home

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 found in Kleven et al. (2024a), having a child does not result in any worsening in labour market outcomes of fathers. 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' skill drop.

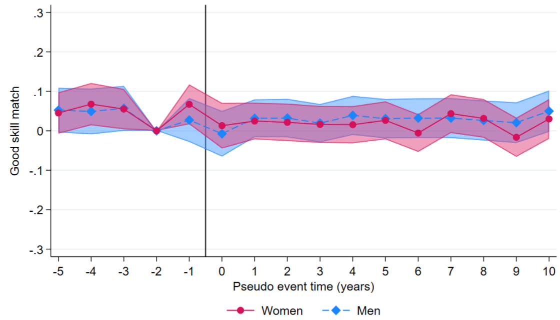
The PIAAC dataset allows to analyse directly how skill use is affected by having children as the survey

[30] The analysis is restricted to respondents currently in employment and therefore includes potential selection effects.

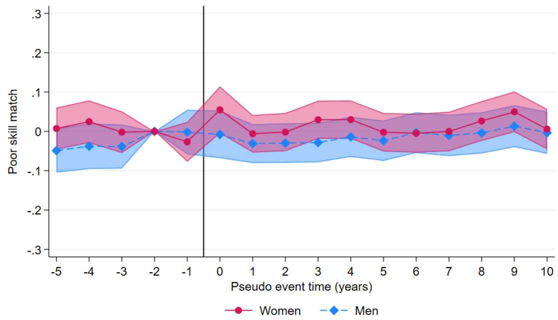
Figure 9: Child penalties in numeracy skill mismatch



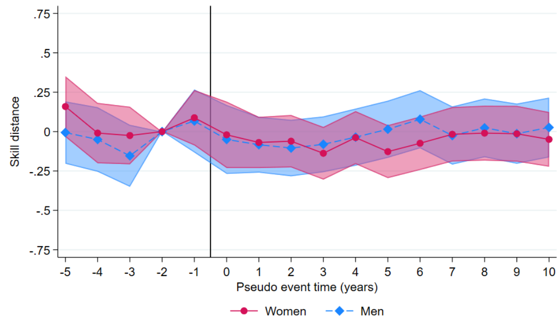
(a) Perfect match (same quintile)



(b) Good match (distance one quintile)



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



(d) Cardinal measure of distance

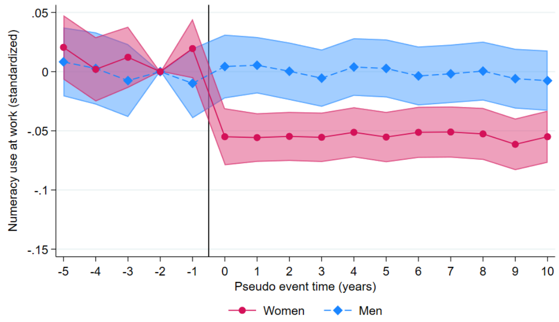
Notes: Figure plots the event-time coefficients α_j obtained from estimating equation (2), together with controls for living with the partner, being born in the country, and education levels. The dependent variables are distances to the country- and occupation-specific as described in section 4.2. Shaded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

collects information on how often skill-related activities are performed.[31] 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.

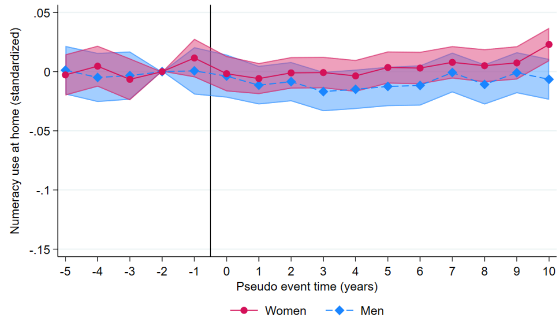
Figure 10 reports event study estimates for numeracy use at work and at home. Panel (a) shows that the use of numeracy skills at work mirrors the employment patterns documented in Figure 4: mothers' numeracy use at work drops significantly and without recovery, while little is going on for fathers. If 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, child penalties in numeracy skill use seem to be entirely driven by labour market participation, but the drop in skill use of mothers does not translate into a larger skill reduction for them which might be explained by increased numeracy use at home. Additionally, time trends in educational attainment seem to contaminate the estimation of child penalties as observed for numeracy skill levels, though to a smaller degree (not shown).

[31] 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.'

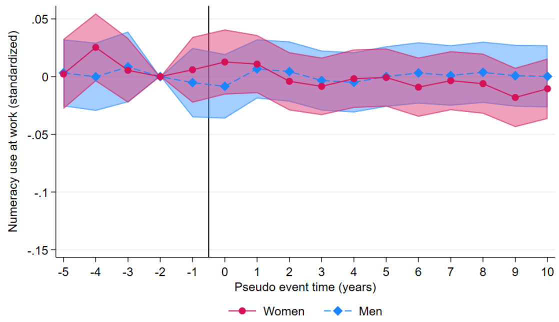
Figure 10: Child penalties in numeracy use at work and in everyday life



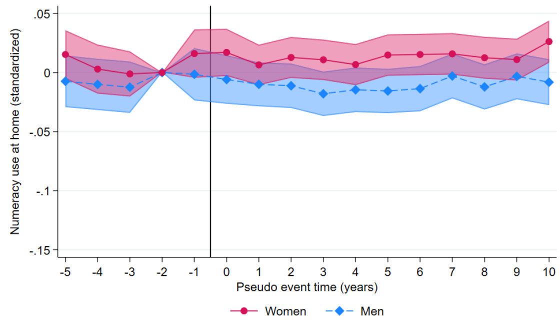
(a) Numeracy use at work



(b) Numeracy use at home



(c) Numeracy use at work (employed respondents)



(d) Numeracy use at home (employed respondents)

Notes: Figure plots the event-time coefficients α_j obtained from estimating equation (2), with and without 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 B.7. Source: PIAAC international PUF

5.2 Survey Response Behaviour

Having a child comes with many changes in life that could lead to a decrease in cognitive skills, regardless of labour market status. Specifically, parents tend to sleep less and with more interruptions,[32] which has been linked to worse cognitive performance (Alhola and Polo-Kantola, 2007).

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.[33] 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, – correctly, or – incorrectly.[34] From this information, we can calculate a share of non-responses for each participant as

[32] Richter et al. (2019) study the sleep duration and satisfaction of parents in Germany and show that both drop substantially after childbirth. Worse sleep is most pronounced three months after childbirth and only fully recovers after six years. Using multinational time-use data by Gershuny et al. (2020) and comparing parents with childless respondents of a similar age, they document that besides the reduction in sleep parents also have substantially less leisure.

[33] 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.11, 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 30s. The smooth distributions give no indication that parents of (young) children are less likely to be part of the sample.

[34] Not all questions are answered by all participants so this variable could be missing because respondents were never

a proxy for skipping skill questions. Overall, leaving more numeracy questions unanswered is related to 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.[35]

5.3 Components of Numeracy Scores

A remaining concern with standardised tests such as PIAAC (or PISA), is the imputation of scores. Not every PIAAC respondent answers all questions in all domains and in fact, some respondents do not answer any numeracy questions at all. These respondents will still be assigned a numeracy score which is calculated from the numeracy performance of observationally similar respondents. Hence, this procedure might reinforce existing differences by any characteristic used in the prediction procedure, including gender. Alternatively, some differences could also be underestimated due to imputation if the latter does not take into account characteristics such as parenthood, which could have a disproportional impact on the scores of one group.

To study this issue, we re-estimate child penalties in numeracy skills using only actual responses of participants. To make this measure more comparable 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).[36] Appendix Figure A.13 shows the equivalent of Figure 7 using the difficulty-weighted share of correct answers among the questions each individual has actually responded to as a numeracy measure. In contrast to the composite score, we estimate that mothers' share of correct responses drops by 4.6 pp (or 6.7% of the sample mean) in the long-term.

Using the actual scores from individual questions also 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 related to the workplace for our analysis, Appendix Figure A.14 shows the child penalty in the 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 5 pp fewer questions correctly compared to fathers.

presented a particular question. This would not be counted as non-response in our measure.

[35] 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.

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

This implies that based on raw responses, we find some evidence for small child penalties in skills. Regrettably, we are unable to further pin down the discrepancy between results based on the aggregate scores and individual responses, but we note that child penalties in the share of correct responses remain small such that extrapolating from the findings of Hanushek et al. (2015), differences in skills could only account for a small share of earnings differences between mothers and fathers.

6 Concluding Remarks

This paper investigates gender differences in the evolution of labour market skills around parenthood. We primarily focus on numeracy skills, and use data from the Survey of Adult Skills of the Programme for the International Assessment of Adult Competencies (PIAAC). To estimate child penalties in labour market skills using this single cross-sectional dataset, we carry out a matching procedure similar to that developed by Kleven (2023). 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). 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 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 entirely disappear when including educational attainment. The absence of 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 by a loss of general labour market-relevant human capital.

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 depreciate faster during parenthood than general skills. If mothers change their job more often after parenthood than fathers (see e.g. Bang and Wang, 2024; Casarico and Lattanzio, 2023), 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.

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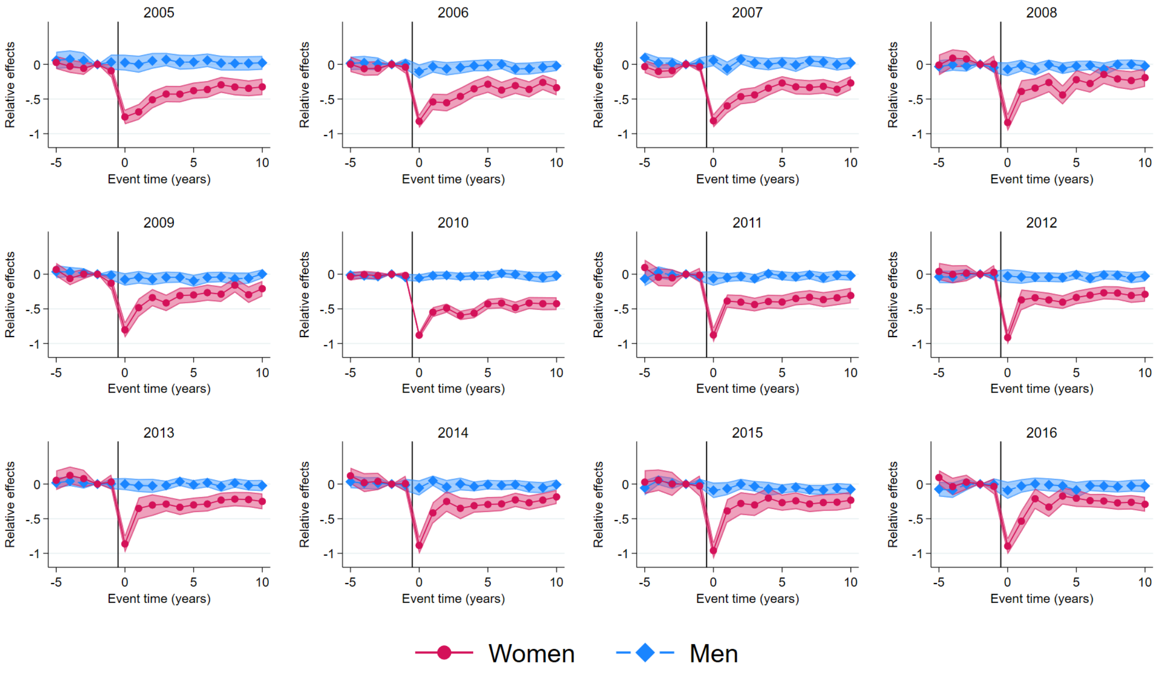
Appendix (for online publication)

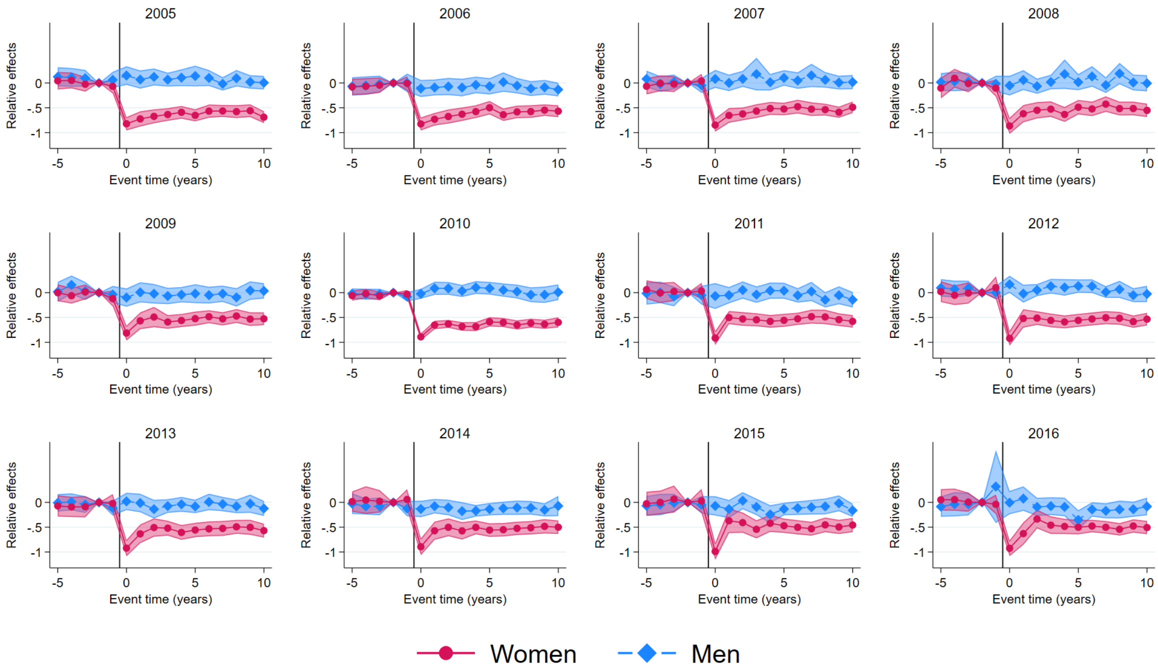
A Figures

Figure A.1: Single cross-sections: Employment



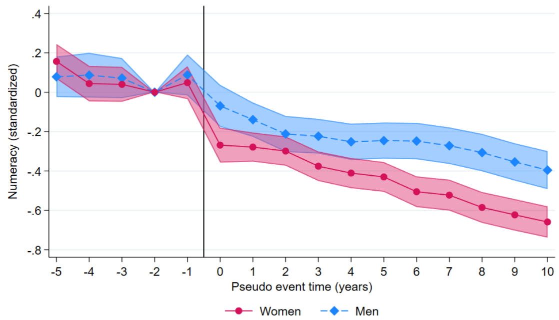
Notes: Plots show the event-time coefficients for a single cross-section as in panel (e) of Figure 3 by year. Source: SOEP-Core, v37

Figure A.2: Single cross-sections: Monthly earnings

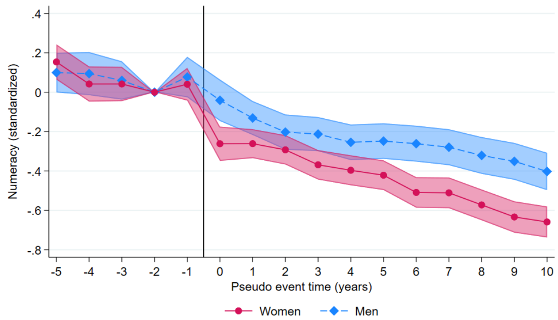


Notes: Plots show the event-time coefficients for a single cross-section as in panel (f) of Figure 3 by year. Source: SOEP-Core, v37

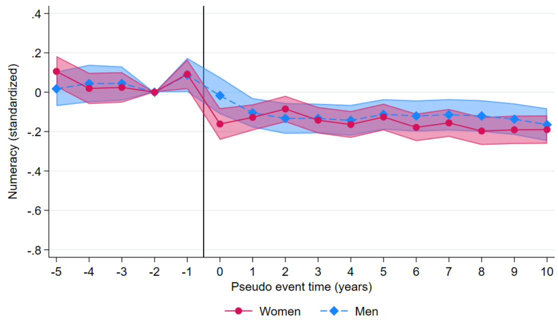
Figure A.3: Child penalties in numeracy scores (with single matching controls)



(a) Controlling for cohabitation



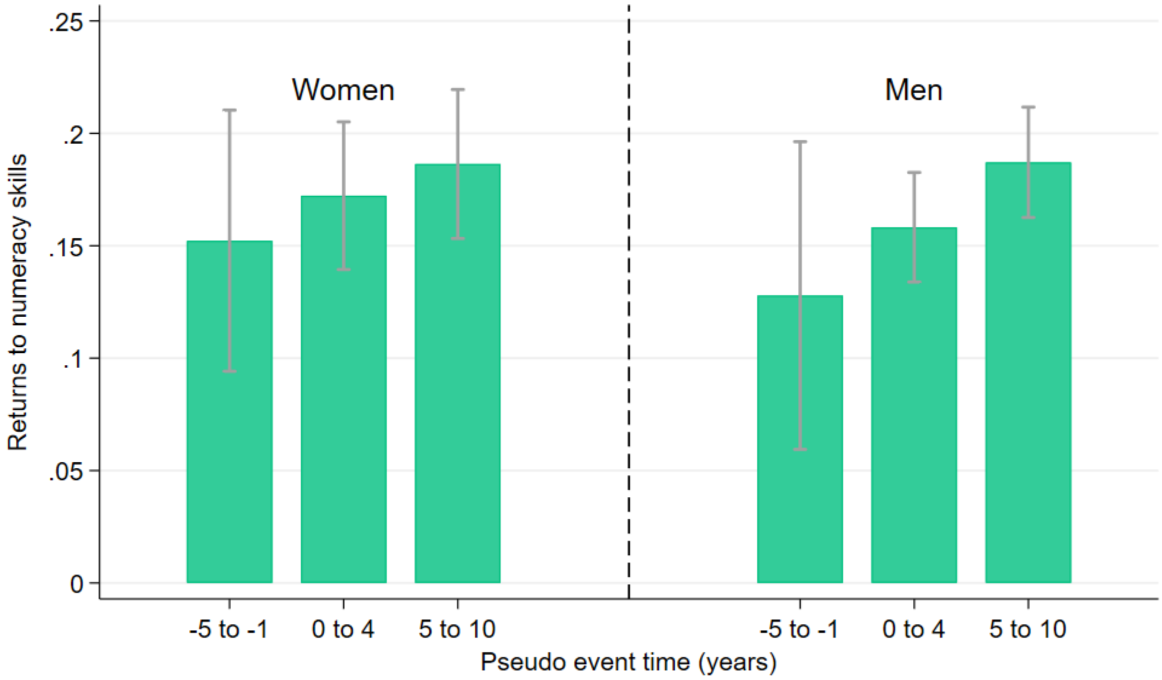
(b) Controlling for being born in the country



(c) Controlling for education

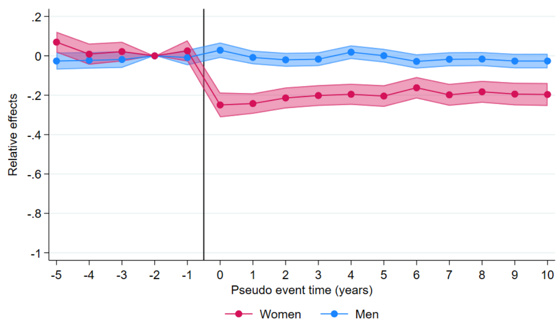
Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2) together with controls for living with the partner, being born in the country, and education levels, respectively. The dependent variable is the standardised numeracy score. Shaded areas represent 95% confidence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

Figure A.4: Returns to skills for (becoming) parents

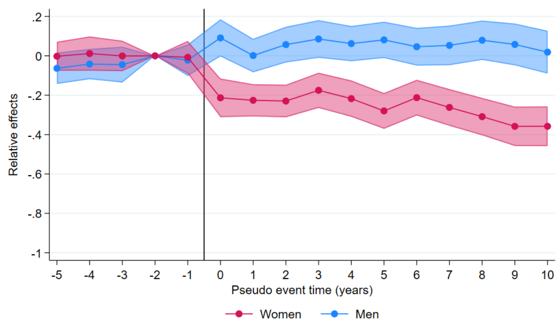


Notes: Figure shows returns to numeracy skills following the methodology by Hanushek et al. (2015). The sample is restricted to respondents in the pseudo event time indicated in the figure and to all employed workers. In Hanushek et al. (2015)'s estimation only full-time workers aged 35-54 enter their sample. We regress the log wage on the numeracy score interacted with the displayed bins of pseudo-event time and additionally control for country fixed effects, experience and experience squared. Standard errors are clustered at the country-level. Range plots represent 95% confidence intervals. Source: PIAAC international PUF

Figure A.5: Child penalties in PIAAC labour market outcomes (with controls)



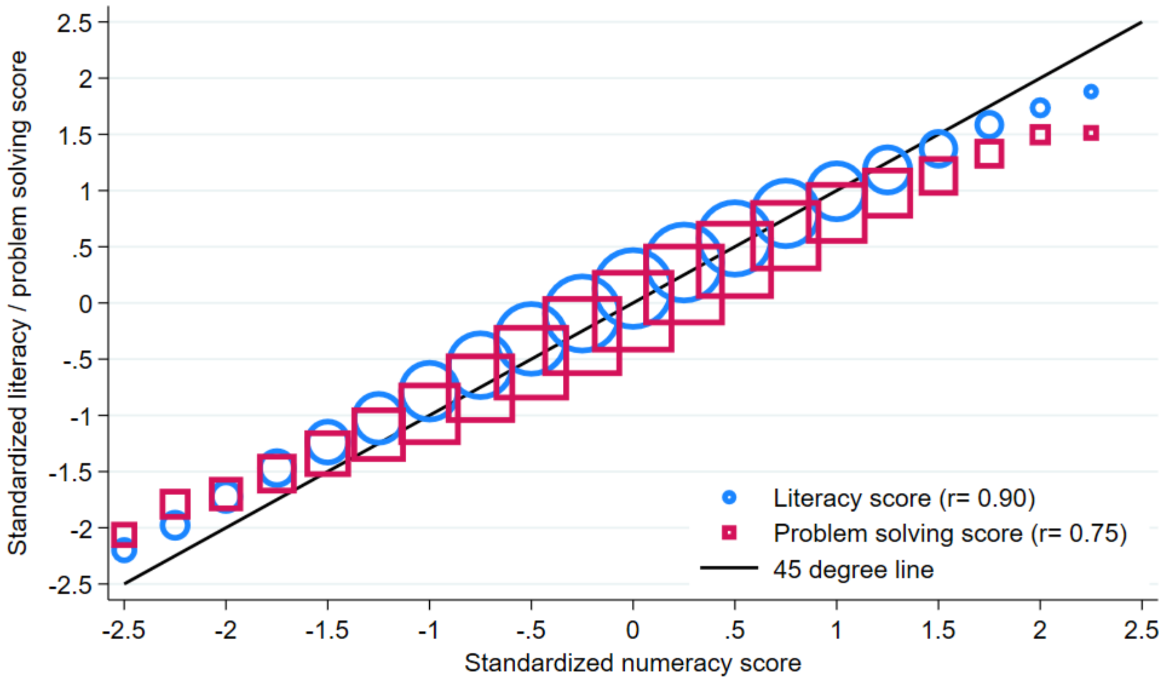
(a) Employment



(b) Monthly earnings

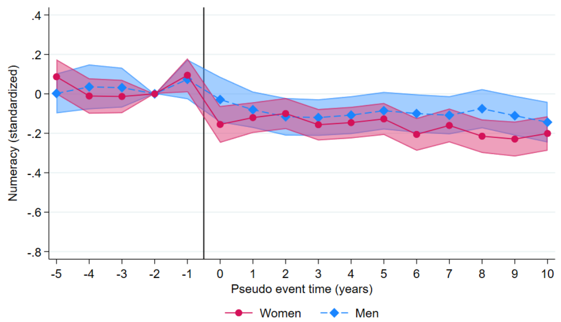
Notes: Plots show the event-time coefficients α_j obtained from estimating equation (2) together with controls for living with the partner, being born in the country, and education levels. Sample in panel (a) consists of all countries listed in Table B.1. Panel (b) omits Hungary, Peru, and Singapore 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

Figure A.6: Correlation of scores

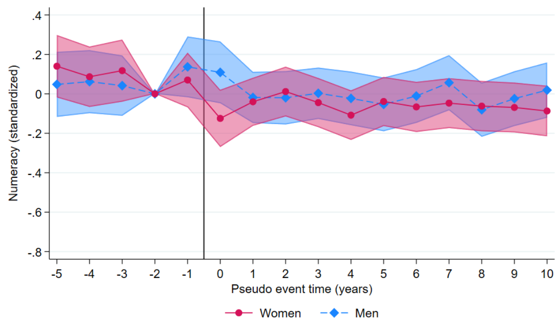


Notes: Size of scatters indicates number of observations per bin. The correlation coefficient refers to the correlation between standardised numeracy score and the respective measures. If the scores were perfectly correlated ($r = 1$) all observations would lie on the 45 degree line. Source: PIAAC international PUF

Figure A.7: Child penalties in numeracy scores by continent



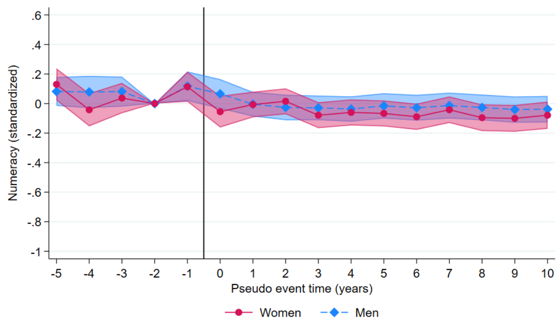
(a) European countries



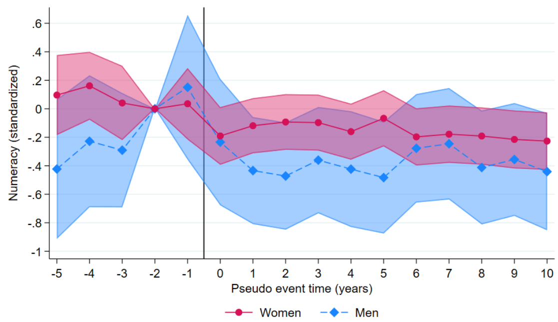
(b) Non-European countries

Notes: Figure shows child penalty estimates for numeracy scores by continent. As 19/29 countries in the sample are from Europe, the diverse set of other countries are pooled in panel (b). Source: PIAAC international PUF

Figure A.8: Child penalties in numeracy scores by employment status



(a) Employed



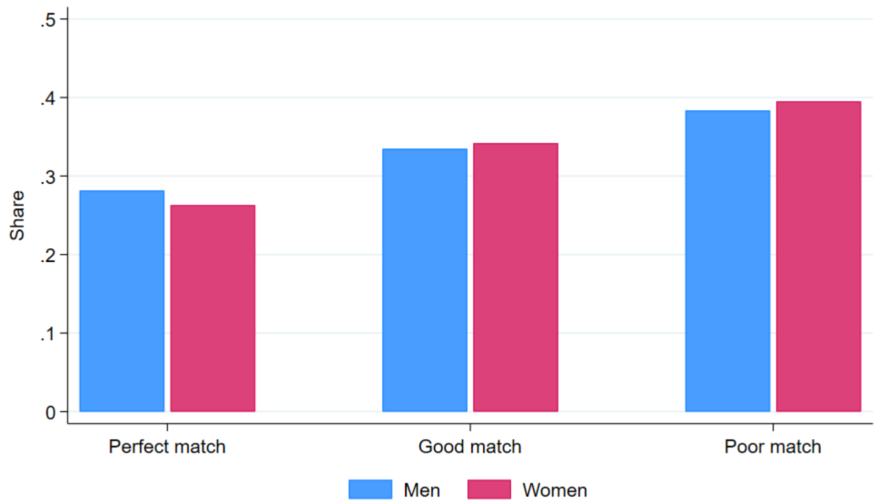
(b) Unemployed

Notes: Figure shows child penalty estimates for numeracy scores by employment status of respondents. Source: PIAAC international PUF

Figure A.9: Skill requirements in occupations

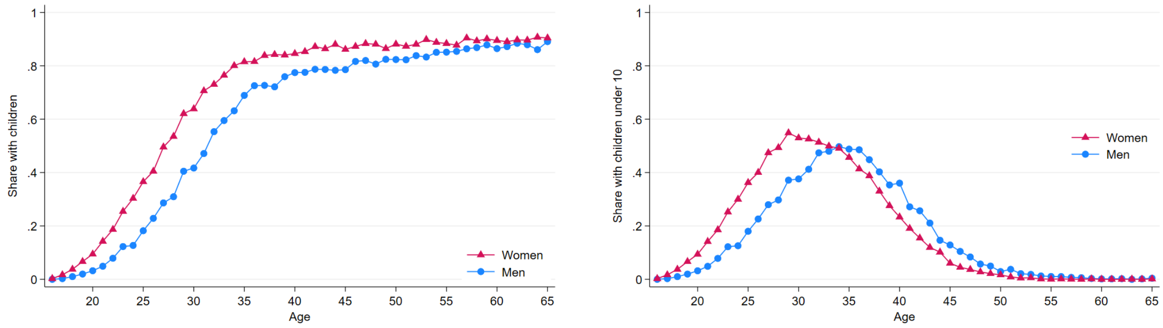
Notes: Bars illustrates the average numeracy skill requirement by 1-digit ISCO occupation. Skill requirements of occupations are obtained following Bandiera et al. (2024) by calculating the frequency of skill use weighted by difficulty for each occupation. The skill requirement indicator ranges from 0 to 1, where 1 means that all six numeracy skills are used in the occupation. Circles indicate the average standardized numeracy score of workers in these occupations. Source: PIAAC international PUF

Figure A.10: Skill (mis-)match by gender



Notes: Figure shows skill (mis-)match by men and women following Bandiera et al. (2024). A perfect match indicates that a workers is in the same numeracy score quintile as the quintile of the job skill requirement. A good match is one quintile apart, a bad match more than one quintile. Source: PIAAC international PUF

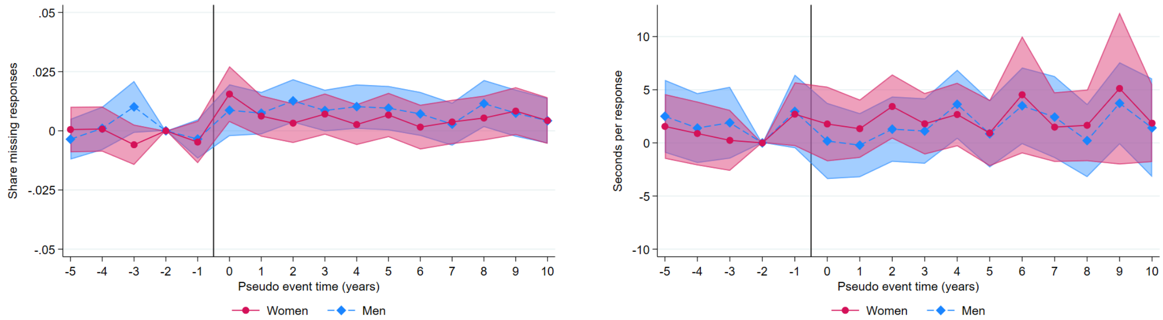
Figure A.11: Share of respondents who are parents by age and gender



(a) Share of respondents with children (b) Share of respondents with children under 10

Notes: Figure reports the share of respondents who have children (panel a) or who have children under the age of 10 (panel b). Source: PIAAC International PUF

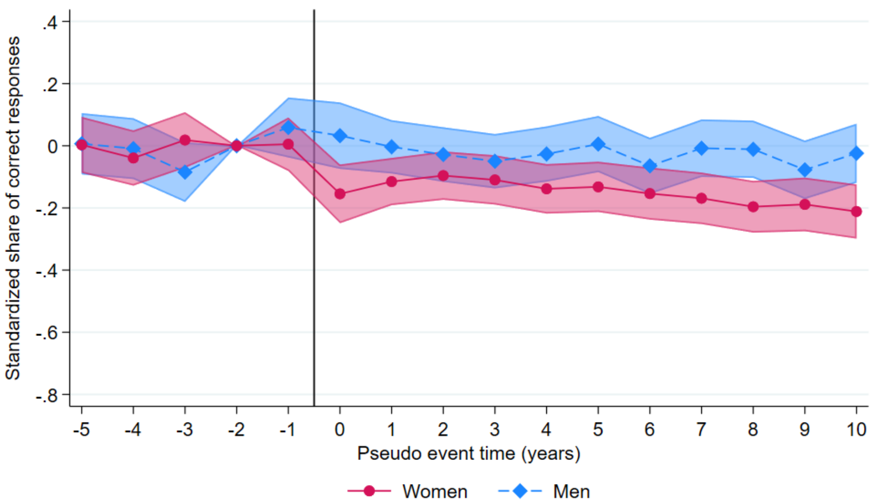
Figure A.12: Child penalties in response behaviour



(a) Share of numeracy questions not answered (b) Average seconds per numeracy question

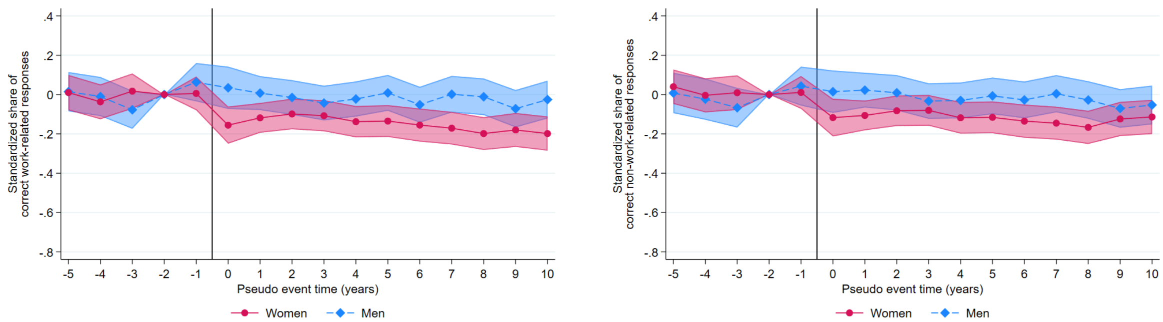
Notes: Figure shows the event-time coefficients α_j obtained from estimating equation (2) together with controls for living with the partner, being born in the country, and education levels. The dependent variables are the share of unanswered numeracy questions and average time per numeracy question (in seconds). Shaded areas represent 95% confidence intervals. Source: PIAAC international PUF

Figure A.13: Child penalties in numeracy scores (actual responses, with 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 variable is the standardized share of numeracy questions answered correctly weighted by the difficulty of the respective items. Shaded areas represent 95% confidence intervals. Source: PIAAC international PUF

Figure A.14: Child penalties in numeracy scores by context



(a) Share of correct answers in work context

(b) Share of correct answers in non-work context

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 standardized share of correctly answered numeracy questions in work and non-work contexts weighted by the difficulty of the respective items. Shaded areas represent 95% confidence intervals. Source: PIAAC international PUF

B Tables

Table B.1: Descriptive Statistics of PIAAC Data

Country	Survey year	First-time parents	First-time mothers	First-time fathers	Median education	Live with partner	Born in country
Belgium	2011/12	29	14	15	4	0.95	0.90
Chile	2014/15	65	41	24	2	0.68	0.98
Czech Republic	2011/12	31	25	6	2	0.81	0.97
Denmark	2011/12	41	15	26	4	0.92	0.71
Ecuador	2017	25	17	8	2	0.73	1.00
Estonia	2011/12	52	26	26	2	0.91	0.95
Finland	2011/12	62	36	26	4	0.93	0.95
France	2011/12	29	12	17	2	0.91	0.86
Greece	2014/15	15	8	7	2	0.92	0.93
Hungary (A,W)	2017	21	9	12	2	0.89	0.97
Ireland	2011/12	37	24	13	3	0.78	0.78
Israel	2014/15	12	5	7	4	0.96	0.82
Italy	2011/12	28	15	13	2	0.92	0.92
Japan	2011/12	58	31	27	4	0.93	1.00
Kazakhstan	2017	26	16	10	3	0.79	0.95
Korea	2011/12	43	22	21	4	0.90	0.98
Lithuania	2014/15	34	22	12	3	0.80	0.99
Mexico	2017	75	38	37	1	0.77	1.00
Netherlands	2011/12	44	17	27	2	0.95	0.93
New Zealand (A)	2014/15	30	18	12	3	0.77	0.71
Norway	2011/12	28	12	16	4	0.89	0.83
Peru (W)	2017	8	3	5	2	0.72	1.00
Poland	2011/12	49	31	18	2	0.89	1.00
Singapore (A,W)	2014/15	14	7	7	4	0.95	0.49
Slovak Republic	2011/12	19	14	5	2	0.92	0.99
Slovenia	2014/15	26	12	14	2	0.95	0.91
Spain	2011/12	35	21	14	2	0.93	0.86
Sweden (W)	2011/12	43	26	17	3	0.93	0.81
United Kingdom	2011/12	100	66	34	2	0.71	0.86
Total	29	1,079	603	476	2	0.85	0.90

Notes: Education levels: 1-lower secondary or less, 2-upper secondary, 3-post-secondary/non-tertiary, 4-tertiary - professional degree, 5-tertiary - bachelor degree, and 6-tertiary - master/research degree; (A) denotes countries where individual age is only available in 5-year intervals, (W) indicates missing monthly earnings (Hungary, Peru, and Singapore) or monthly earnings only reported in deciles (Sweden).

Table B.2: Descriptive statistics of the estimation sample (age)

	Men			Women		
Event time	Age p10	Median age	Age p90	Age p10	Median age	Age p90
-5	19	27	33	19	25	31
-4	18	27	34	19	25	32
-3	19	27	34	19	25	32
-2	20	28	35	19	26	32
-1	21	29	35	19	26	33
0	22	30	37	21	28	35
1	22	31	39	21	28	36
2	24	32	40	22	29	37
3	24	32	41	23	30	37
4	26	33	41	23	30	38
5	27	35	42	25	32	40
6	27	36	44	25	33	40
7	28	37	44	26	33	41
8	29	37	45	27	35	42
9	31	38	47	28	35	43
10	32	39	47	29	36	44

Notes: Age of male and female respondents in event times -5 to 10; 10th, 50th, and 90th percentile. Positive event times are calculated using the age of the first child. Negative event times represent the pseudo panel generated as described in section 3. Hungary, New Zealand, and Singapore only offer age information in 5-year brackets such that we assign individuals the age of the midpoint in the respective interval.

Table B.3: Descriptive statistics of the estimation sample (education)

	Men			Women		
Event time	Lower secondary or less	Upper & post-secondary	Tertiary	Lower secondary or less	Upper & post-secondary	Tertiary
-5	0.15	0.50	0.35	0.06	0.44	0.50
-4	0.18	0.49	0.33	0.08	0.44	0.47
-3	0.18	0.49	0.32	0.07	0.43	0.49
-2	0.19	0.46	0.35	0.09	0.41	0.50
-1	0.18	0.46	0.36	0.10	0.43	0.47
0	0.19	0.43	0.38	0.11	0.41	0.49
1	0.17	0.43	0.40	0.14	0.39	0.47
2	0.17	0.45	0.38	0.15	0.44	0.41
3	0.18	0.43	0.38	0.13	0.40	0.47
4	0.18	0.44	0.38	0.15	0.39	0.46
5	0.18	0.43	0.39	0.15	0.41	0.43
6	0.19	0.41	0.41	0.17	0.38	0.45
7	0.19	0.43	0.39	0.17	0.39	0.43
8	0.20	0.41	0.39	0.18	0.39	0.43
9	0.23	0.41	0.36	0.20	0.40	0.40
10	0.22	0.44	0.34	0.21	0.41	0.38

Notes: Shares of male and female respondents in event times -5 to 10 for each education level: lower secondary or less, upper & post-secondary, and tertiary. Positive event times are calculated using the age of the first child. Negative event times represent the pseudo panel generated as described in section 3.

Table B.4: Summary estimates for child penalties in numeracy (without matching controls)

	Men	Women	Women-Men
	(1)	(2)	(3)
Pre-birth	0.0398	0.0491*	0.0093
	(0.0350)	(0.0284)	(0.0451)
Short-term effect	-0.2480***	-0.3597***	-0.1117***
	(0.0305)	(0.0241)	(0.0389)
Long-term effect	-0.3600***	-0.5733***	-0.2134***
	(0.0322)	(0.0255)	(0.0411)
Observations	14,824	18,701	33,525

Notes: Table shows summary estimates for child penalties in numeracy scores corresponding to event-time coefficients presented in Figure 5. The omitted category is two years before birth. Source: PIAAC international PUF

Table B.5: Summary estimates for child penalties in literacy and problem-solving scores (with controls)

Dep. variable:	Literacy skills			Problem-solving skills		
	Men	Women	Men-women	Men	Women	Men-women
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-birth	-0.0076	0.0096	0.0172	-0.0067	0.0242	0.0309
	(0.0288)	(0.0251)	(0.0382)	(0.0348)	(0.0292)	(0.0455)
Short-term effect	-0.1752***	-0.1545***	0.0207	-0.2123***	-0.2133***	-0.0009
	(0.0259)	(0.0221)	(0.0340)	(0.0313)	(0.0259)	(0.0406)
Long-term effect	-0.1844***	-0.1976***	-0.0132	-0.2508***	-0.3169***	-0.0661
	(0.0275)	(0.0238)	(0.0363)	(0.0333)	(0.0282)	(0.0437)
Observations	13,624	17,693	31,317	9,902	12,979	22,881

Notes: Table shows summary estimates for child penalties in literacy and problem solving scores corresponding to event-time coefficients presented in Figure 8. The pre-birth periods covers event-time -5 to -3, the short term estimate is 0 to 4 years, and the long-term estimate 5 to 10 years. The two years before birth is the omitted category. Source: PIAAC international PUF

Table B.6: Summary estimates for child penalties in skill matches (with matching controls)

	Men	Women	Women-Men	Men	Women	Women-Men
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Perfect skill matches			Good skill matches		
Pre-birth	0.0009	-0.0455***	-0.0465**	0.0394**	0.0214	-0.0180
	(0.0173)	(0.0155)	(0.0232)	(0.0190)	(0.0174)	(0.0257)
Short-term effect	0.0117	-0.0140	-0.0257	0.0122	-0.0156	-0.0278
	(0.0154)	(0.0146)	(0.0212)	(0.0164)	(0.0157)	(0.0227)
Long-term effect	-0.0100	-0.0067	0.0033	0.0161	-0.0156	-0.0317
	(0.0162)	(0.0158)	(0.0226)	(0.0172)	(0.0169)	(0.0241)
Observations	12,885	12,678	25,563	12,885	12,678	25,563
Panel B:	Poor skill matches			Skill distance		
Pre-birth	-0.0404**	0.0241	0.0645**	-0.1062	-0.0064	0.0999
	(0.0186)	(0.0174)	(0.0254)	(0.0649)	(0.0608)	(0.0889)
Short-term effect	-0.0239	0.0296*	0.0536**	-0.1080*	-0.1186**	-0.0106
	(0.0166)	(0.0157)	(0.0228)	(0.0587)	(0.0537)	(0.0796)
Long-term effect	-0.0061	0.0224	0.0285	-0.0162	-0.0987*	-0.0824
	(0.0175)	(0.0168)	(0.0243)	(0.0616)	(0.0572)	(0.0841)
Observations	12,885	12,678	25,563	12,885	12,678	25,563

Notes: Table shows summary estimates for child penalties in skill matches corresponding to event-time coefficients presented in Figure 9. The omitted category is two years before birth. Source: PIAAC international PUF

Table B.7: Summary estimates for child penalties in numeracy use at work and in everyday life (with matching controls)

	Men	Women	Women-Men	Men	Women	Women-Men
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Numeracy use at work			Numeracy use at home		
Pre-birth	0.0057	0.0016	-0.0041	-0.0026	-0.0072	-0.0047
	(0.0100)	(0.0087)	(0.0132)	(0.0067)	(0.0057)	(0.0088)
Short-term effect	0.0067	-0.0642***	-0.0708***	-0.0124**	-0.0092**	0.0032
	(0.0083)	(0.0071)	(0.0109)	(0.0056)	(0.0046)	(0.0072)
Long-term effect	0.0033	-0.0641***	-0.0674***	-0.0076	0.0010	0.0086
	(0.0086)	(0.0074)	(0.0114)	(0.0058)	(0.0048)	(0.0075)
Observations	11,606	15,775	27,381	12,189	16,191	28,380
Panel B:	Numeracy use at work (employed)			Numeracy use at home (employed)		
Pre-birth	-0.0026	-0.0072	-0.0047	-0.0092	-0.0027	0.0066
	(0.0067)	(0.0057)	(0.0088)	(0.0078)	(0.0072)	(0.0106)
Short-term effect	-0.0124**	-0.0092**	0.0032	-0.0120*	0.0016	0.0136
	(0.0056)	(0.0046)	(0.0072)	(0.0063)	(0.0059)	(0.0086)
Long-term effect	-0.0076	0.0010	0.0086	-0.0087	0.0076	0.0162*
	(0.0058)	(0.0048)	(0.0075)	(0.0065)	(0.0061)	(0.0089)
Observations	12,189	16,191	28,380	10,707	9,861	20,568

Notes: Table shows summary estimates for child penalties in numeracy use at work and at home corresponding to event-time coefficients presented in Figure 10. The omitted category is two years before birth. Source: PIAAC international PUF