

# Skill loss during parental leave and its role for gender disparities in earnings

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This study provides a missing puzzle piece for understanding the persistent gender differences in earnings. Prior research has shown that the longer child-related career interruptions of mothers are related to their lower income, but the mechanisms behind this link are still unclear. One explanation could be that mothers lose work-related skills during extended parental leave; however, empirical evidence for this link is missing. We aim at filling this research gap by investigating whether human capital depreciation during parental leave widens the gender disparities in earnings. The analysis is based on a longitudinal dataset for German adults, which matches administrative data on income and labour market histories with test scores on work-related skills. It allows us to investigate tested competencies of parents before and after the birth of their child, and before and after they go on parental leave, using panel data regression analysis. Our sample consists of 9,796 adults aged 20 to 45 between 2010 and 2022. Preliminary results suggest that the birth of a child decreases work-related skills of mothers, but not of fathers; however, effects sizes are small. We find no heterogeneities by birth rank, the number of births, or skill domain. In future analyses, we will further differentiate based on parental leave duration and subsequent income. The findings will offer important insights for shaping parental leave policies and tackling skilled labour shortages.

**JEL classification:** J24, J13, J16

**Keywords:** human capital, parental leave, work-related skills, gender earnings gap

## 1 Introduction

Human capital is a major determinant of individual labour market outcomes. Differences in education, experience, health, and skills are frequently identified as main factors explaining disparities in income and employment. Recent evidence suggests that returns to work-related cognitive skills are particularly large. For example, a study on OECD countries found that a one-standard-deviation increase in numeracy or literacy skills raises wages by an average of 18% (Hanushek et al., 2015).

These work-related skills change throughout the life course (Reiter, 2022). Major life events – like the birth of a child – have the potential to alter them, at least tem-

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porarily. Test scores from the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills suggest that parents have consistently lower numeracy, literacy, and problem-solving skills than childless adults (authors' calculation based on PIAAC data). Differences are most pronounced during child-bearing ages and tend to be larger for women than for men. This pattern is in line with earlier research that found higher job-related skill scores among men compared to women (Christl & Köppl-Turyna, 2020; Rebollo-Sanz & De la Rica, 2022). It is unclear what drives this gap in human capital between parents and non-parents, and between mothers and fathers. Although often suggested, pregnancy alone cannot explain the drop in mothers' cognitive skills (Christensen et al., 2010); however, existing literature provides little evidence for alternative explanations.

One hitherto unexplored reason for the lower work-related skills of parents, in particular mothers, could be skill depreciation during parental leave.<sup>1</sup> This hypothesis is backed up by evidence from Sweden, which shows that time away from the job reduces cognitive skills and wages (Edin & Gustavsson, 2008). The literature on the gender wage gap has long suggested potential skill losses during prolonged parental leave as a mechanism for gender differences in earnings (Tharp & Parks-Stamm, 2021; Pertold-Gebicka 2020; Evertsson 2016; Görlich & de Grip 2009; Mincer & Polachek, 1974). However, there is no empirical evidence for a link between longer parental leave, human capital depreciation, and the lower income of women.

We fill this important research gap by answering the research question “Does skill loss during parental leave contribute to gender disparities in earnings?” We hypothesise that work-related skills decrease during parental leave and that the longer leave duration of women is one reason for the gender gap in job skills. We further hypothesise that gender differences in leave duration and subsequent human capital loss contribute to the gender gap in earnings.

The study takes a novel approach by analysing a matched dataset that combines detailed administrative data from Germany with test scores on work-related competencies from the German National Educational Panel Study (NEPS). Such test results are increasingly used to measure human capital, especially work-related cognitive skills like numeracy and literacy (Christl & Köppl-Turyna, 2020; Hanushek et al., 2015; Rebollo-Sanz & De la Rica, 2022). By adding register data to the tested skills data, we gain additional information on employment and income histories that are less prone to measurement error than self reports from surveys. The longitudinal

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<sup>1</sup>For now, we use this term to refer to both maternity and parental leave.

data further allows us to account for unobserved heterogeneity via panel data methods.

Our findings will inform the ongoing discussion on the reconciliation of family and work across demography, economics, and other fields of research that evaluate family-related policies. Primarily, we contribute to the multidimensional evaluation of parental leave policies and their ambiguous effects on the labour market outcomes of parents. Our research will help assessing statutory leave duration from a policymaker’s perspective, who has to balance care and protection during significant life events, financial aspects, workforce productivity, and broader societal objectives such as gender equity.

This study is also highly relevant in light of demographic change and the current skill shortages across high-income countries. Exploiting existing human capital potentials is considered a promising strategy to address the shrinking skilled labour force. Here, increasing the labour market participation of mothers is often seen as an important lever. Our study will assess whether long parental leave has an impact that goes beyond the mere absence of skilled mothers, i.e. whether parental leave is linked to skill depreciation. The results may also prove important at the organisational level, where skill maintenance strategies are essential for companies to manage skill erosions during parental leave and other career interruptions.

## **2 Literature**

This study expands several strands of literature in economics and demography. Most directly, it contributes to the multidimensional assessment of family-related policies and their ambiguous impact on parents’ labour market outcomes. Evidence on the effect of parental leave duration on income and employment is inconclusive. Overall, shorter parental leave appears to have a positive impact on mothers’ economic outcomes, while some studies find negative effects once parental leave is too long (Olivetti & Petrongolo, 2017). Relatedly, the longer career interruptions of mothers are crucial for explaining the gender wage gap (Blau & Kahn, 2017); although for Austria, Kleven et al. (forthcoming) find only a short-term negative impact on the motherhood penalty. However, even temporary drops in earnings may – depending on the pension system – result in lower income during retirement (Hammer et al., 2020).

Little is known about the mechanisms between longer parental leave and subsequent earnings. Here we focus on human capital depreciation during parental leave as one potential mediator between parenthood and income. Our study thus also contributes to the literature on the returns to human capital, which has traditionally been opera-

tionalised as formal education and later health status, but was then also extended to cognitive, non-cognitive (Heckman et al., 2006), and social skills. More recent work in economics and demography measures human capital based on tested competencies (Lutz et al., 2021; Rebollo-Sanz & De la Rica, 2022; Reiter, 2022) and finds substantial returns to numeracy and literacy skills (Hanushek et al., 2015). Time away from the job, however, can erode skills and earnings (Edin & Gustavsson, 2008), which is why we believe that the hitherto unexplored link between parental leave duration and job skills may prove important for understanding the effect of child-related career interruptions on labour market outcomes.

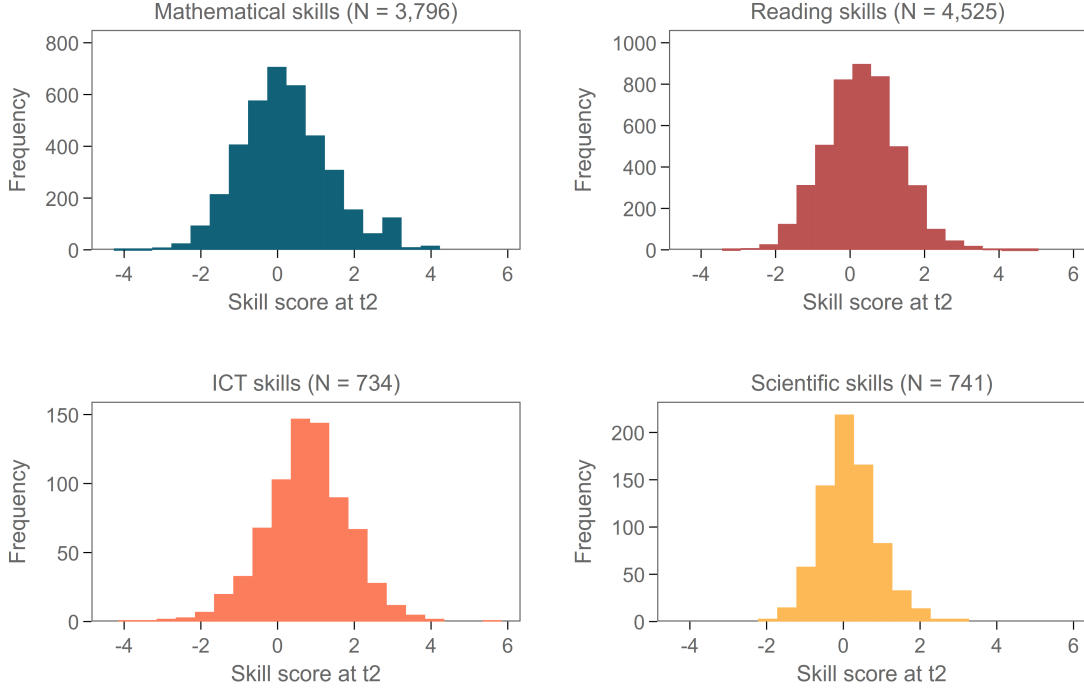
This study also relates to the literature on the gender wage gap. Recent evidence based on tested skills found that the higher scores of men are important in explaining gender differences in wages (Christl & Köppl-Turyna, 2020; Rebollo-Sanz & De la Rica, 2022). However, none of this earlier work has investigated human capital depreciation during parental leave as a mechanism for gender differences in skills and subsequent income.

Finally, a recent paper by Kawaguchi and Toriyabe (2022) explored skill use in OECD labour markets. They found that longer statutory parental leave is associated with increased skill use for lower-skilled women, but with skill underutilisation for higher-skilled women. While they did not explore the relationship between parental leave and work-related skills directly, their results point towards an important link between family-related policies and human capital allocation.

### 3 Data

Our analysis is based on a rich dataset from NEPS, a nationally representative panel study designed to explore skill development, labour market trajectories, and fertility and family formation across the entire life course in Germany. In addition to a rich set of socio-demographic variables, NEPS provides test scores on competencies that adults need to advance at work, including mathematical competence, reading competence, scientific competence, and information and communications technology competence. These skill dimensions are increasingly used in the literature to measure human capital and to estimate its returns (Hanushek et al., 2015; Rebollo-Sanz & De la Rica, 2022). NEPS' longitudinal data structure allows us to investigate the participants' skills at different waves and thus before and after the birth of a child, and before and after they take parental leave. In other words: We observe changes in the level of skills between two measurement points  $t_1$  and  $t_2$ , and whether

Figure 1: Skill scores by domain at  $t_2$



a birth happened between these measurement points. The change in skills is defined as  $\Delta\text{Skills} = \text{Skill score at } t_2 - \text{Skill score at } t_1$ .

Our sample includes individuals in their reproductive age that were aged 18 to 45 years old when they participated in their first test ( $t_1$ ) and no younger than 18 years old at first birth. This results in a sample of 9,796 observations of which 1,383 experienced at least one birth between  $t_1$  and  $t_2$ . The skill assessments took place between 2010 and 2022 and the difference between  $t_1$  and  $t_2$  can be up to ten years (see Figure A.1 of the Appendix). We account for these variations in our regression models. Skill scores are weighted and scaled, going from about -5 to +5, as shown in Figure 1.

NEPS can be linked with administrative data on employment histories, including information on absence from work, earnings, and benefits, going back as far as to 1975. Most importantly, the register data provides us with high-quality income data over the life course, which is more reliable than the self reports from surveys. The results in this draft are not yet based on the administrative data, but on the survey data only.

## 4 Empirical strategy

We investigate whether skill loss during parental leave widens the gender gap in earnings. We model changes in skill scores ( $\Delta\text{Skills}$ ) of individual  $i$  between two measurement points ( $t_1$  and  $t_2$ ) as a function of birth (and later parental leave duration), gender, formal education at  $t_1$ , the change in formal education between  $t_1$  and  $t_2$ , and a set of control variables  $X$ , thereby following Edin & Gustavsson (2008).

$$\Delta\text{Skills}_i = \beta_0 + \beta_1\text{Birth}_i + \beta_2\text{Gender} + \beta_3\text{Education at } t_{1i} + \beta_4\Delta\text{Education}_i + \beta_5X_i + \varepsilon$$

$\Delta\text{Skills}$  is either a dummy variable indicating an increase or decrease in skills between  $t_1$  and  $t_2$ , or a continuous variable indicating the difference in skills between  $t_1$  and  $t_2$ . Vector  $X$  includes age at  $t_1$ , the number of children of individual  $i$ , migration status, the skill domain, time between birth and  $t_2$ , the survey cohort, and the survey year at  $t_2$ . In robustness analyses, we control for the skill level, to further account for floor and ceiling effects. We also estimate this equation separately for women and men, and separately for parents that have their first child versus subsequent children. Summary statistics are provided in Table A.1 of the Appendix.

## 5 Preliminary results

This section provides preliminary results based on NEPS data. Comparing  $\Delta\text{Skills}$  for those who experience no birth between  $t_1$  and  $t_2$  with those who experience at least one birth between  $t_1$  and  $t_2$  shows that the drop in skills is larger for those had a child between the two test (Table 1). More specifically, the differences between those who had no child and those who had a child is -0.027 for women and -0.073 for men. Given the range of skill scores from -5 to +5, however, these changes are almost negligibly small.

Table 1: The change in skill scores between  $t_1$  and  $t_2$

	Without birth between $t_1$ and $t_2$	With birth between $t_1$ and $t_2$	Difference
Women	0.030	-0.057	-0.027
Men	-0.003	-0.070	-0.073

Notes: This table provides the change in skill scores  $\Delta\text{Skills}$  between  $t_1$  and  $t_2$  for women and men who experience no birth between  $t_1$  and  $t_2$ , and for women and men who experienced at least one birth between  $t_1$  and  $t_2$ . It also shows the difference between those groups.

Table 2: The effect of births on skill changes between the first ( $t_1$ ) and second ( $t_2$ ) test

	Women		Men	
	Skills drop	$\Delta$ Skills	Skills drop	$\Delta$ Skills
<b>Birth between <math>t_1</math> and <math>t_2</math></b>	<b>0.554**</b>	<b>-0.183*</b>	<b>0.414</b>	<b>-0.115</b>
	(0.261)	(0.097)	(0.299)	(0.159)
Medium education $t_1$ (vs. low)	0.841**	-0.256	0.471	-0.386***
	(0.351)	(0.162)	(0.328)	(0.149)
High education $t_1$ (vs. low)	0.791**	-0.279*	0.719**	-0.583***
	(0.364)	(0.169)	(0.357)	(0.166)
$\Delta$ Education	0.013	-0.005	0.008	-0.011
	(0.025)	(0.012)	(0.027)	(0.014)
Additional control variables	Yes	Yes	Yes	Yes
Mean Y	0.48	0.04	0.49	0.02
N	5,607	5,607	4,051	4,051

Note: The table shows the effect of any birth on the probability that skills decrease between  $t_1$  and  $t_2$  (Logit; first column) and on the difference in skills between  $t_2$  and  $t_1$  (OLS; second column). Additional control variables include age in 5-year-categories, the skill domain, the number of children, migration status, the time between the birth and  $t_2$ , the survey cohort, and the survey year at  $t_2$ . Weights are applied; standard errors are clustered at the individual level and given in parentheses; \*  $p \leq 0.10$ , \*\*  $p \leq 0.05$ , \*\*\*  $p \leq 0.01$

The regression results in Table 2 suggest that the birth of a child increases the likelihood of a skill drop for women between the two measurement points (+0.554) and decreases their skills (-0.183). However, similar to the descriptive results above, these estimates have to be considered very small. We find no significant difference in  $\Delta\text{Skills}$  between men who had children, and those who did not.

We find no heterogeneities in the effects by birth rank (Figure A.2 of the Appendix) or the number of births between  $t_2$  and  $t_1$  (Figure A.3 of the Appendix). The large standard errors make it infeasible to assess effect heterogeneities by skill domain (Figure A.4 of the Appendix).

## 6 Discussion and outlook

Our findings suggest that the often-suspected depreciation of work-related skills during extended career interruptions is unlikely an important driver for the lower income of mothers. While the negative impact of childbirth on mothers' work-related cognitive skills is concerning, the estimated effects are too small to explain the large gender differences in wages. However, the findings are highly relevant in light of the current skill shortages. Exploiting existing human capital potentials is considered a promising strategy to address the shrinking skilled labour force. Here, increasing the labour market participation of mothers is often seen as an important lever. Our findings suggest that by decreasing skills, extensive parental leave has an impact that goes beyond the mere absence of skilled mothers.

To explore if changes in work-related skills explain gender differences in earnings, we will – in a next step – match NEPS with German administrative data on income and labour market histories. This study will thus not only contribute to the knowledge on human capital depreciation during career breaks, but also its role for the gender wage gap – a link that is frequently hinted at in the literature, but was never addressed directly. In addition, we will investigate how a large parental leave policy affected the gender gap in both skills and earnings, which has wide-ranging implications for policymaking.



## References

- Bergemann, A., & Riphahn, R. T. (2023). Maternal employment effects of paid parental leave. *Journal of Population Economics*, 36(1), 139–178. <https://doi.org/10.1007/s00148-021-00878-7>
- Blau, F. D., & Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, 55(3), 789–865. <https://doi.org/10.1257/jel.20160995>
- Christensen, H., Leach, L. S., & Mackinnon, A. (2010). Cognition in pregnancy and motherhood: Prospective cohort study. *British Journal of Psychiatry*, 196(2), 126–132. <https://doi.org/10.1192/bjp.bp.109.068635>
- Christl, M., & Köppl-Turyna, M. (2020). Gender wage gap and the role of skills and tasks: Evidence from the Austrian PIAAC data set. *Applied Economics*, 52(2), 113–134. <https://doi.org/10.1080/00036846.2019.1630707>
- Edin, P.-A., & Gustavsson, M. (2008). Time Out of Work and Skill Depreciation. *Industrial and Labor Relations Review*, 61(2), 163–180. <https://doi.org/10.1177/001979390806100202>
- Hammer, B., Spitzer, S., Vargha, L., & Istenič, T. (2020). The gender dimension of intergenerational transfers in Europe. *The Journal of the Economics of Ageing*, 15, 100234. <https://doi.org/10.1016/j.jeo.a.2019.100234>
- Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, 73, 103–130. <https://doi.org/10.1016/j.eurocorev.2014.10.006>
- Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, 24(3), 411–482. <https://doi.org/10.1086/504455>
- Kawaguchi, D., & Toriyabe, T. (2022). Measurements of skill and skill-use using PIAAC. *Labour Economics*, 78, 102197. <https://doi.org/10.1016/j.labeco.2022.102197>
- Kleven, H., Landais, C., Posch, J., Steinhauer, A., & Zweimüller, J. (forthcoming).

Do Family Policies Reduce Gender Inequality? Evidence from 60 Years of Policy Experimentation. *American Economic Journal: Economic Policy*.

Lutz, W., Reiter, C., Özdemir, C., Yildiz, D., Guimaraes, R., & Goujon, A. (2021). Skills-adjusted human capital shows rising global gap. *Proceedings of the National Academy of Sciences*, 118(7), e2015826118. <https://doi.org/10.1073/pnas.2015826118>

Olivetti, C., & Petrongolo, B. (2017). The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-Income Countries. *Journal of Economic Perspectives*, 31(1), 205–230. <https://doi.org/10.1257/jep.31.1.205>

Rebollo-Sanz, Y. F., & De la Rica, S. (2022). Gender gaps in skills and labor market outcomes: Evidence from the PIAAC. *Review of Economics of the Household*, 20(2), 333–371. <https://doi.org/10.1007/s11150-020-09523-w>

Reiter, C. (2022). Changes in Literacy Skills as Cohorts Age. *Population and Development Review*, 48(1), 217–246. <https://doi.org/10.1111/padr.12457>

## Appendix

Figure A.1: Time difference between  $t_1$  and  $t_2$

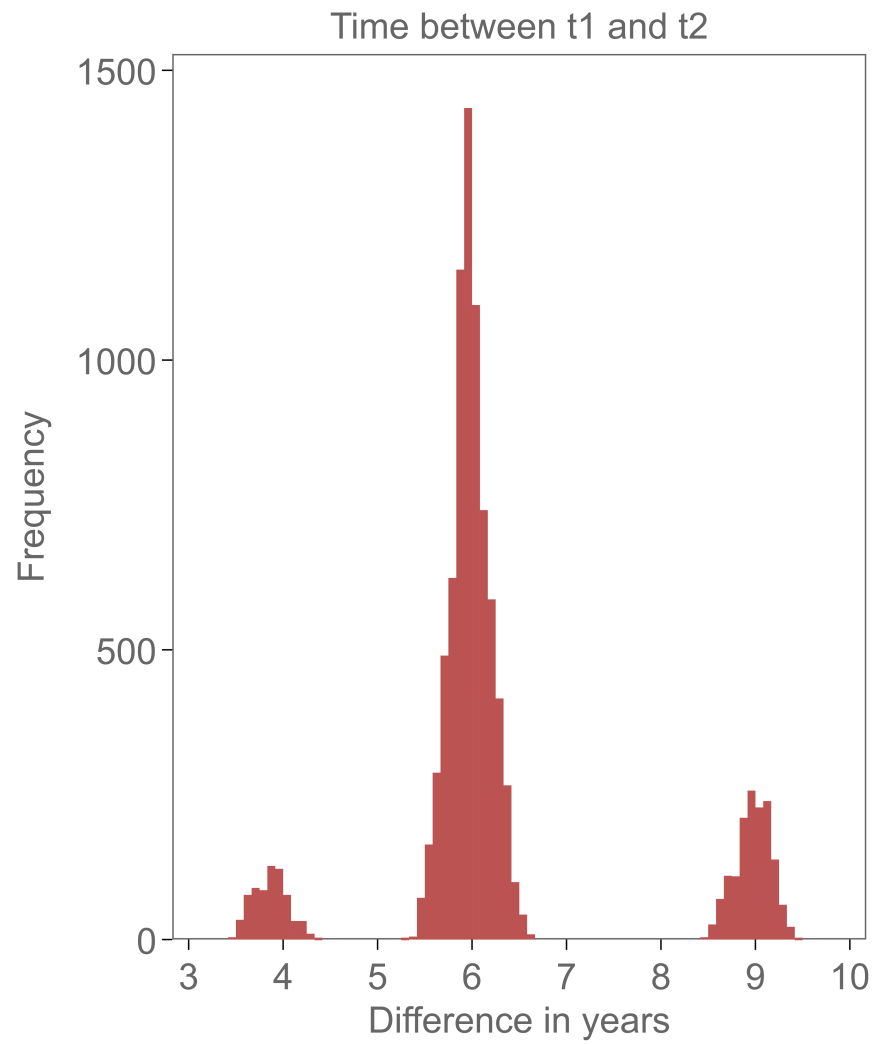
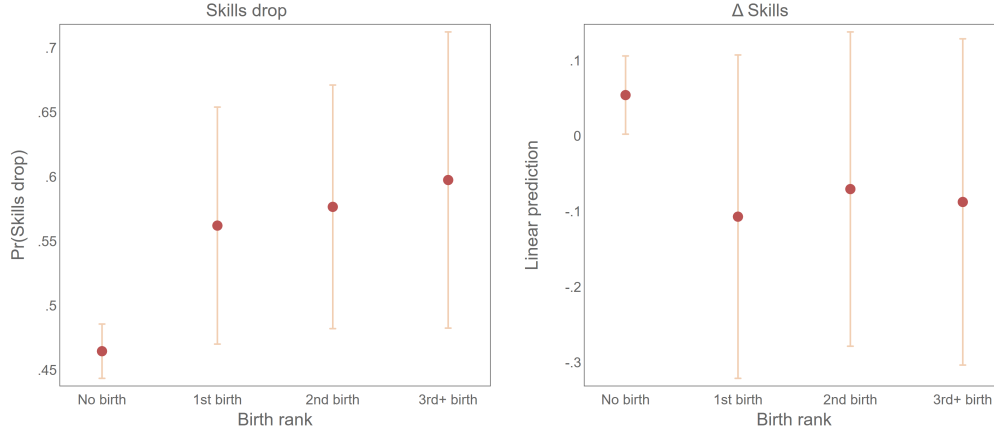


Table A.1: Summary table (unweighted)

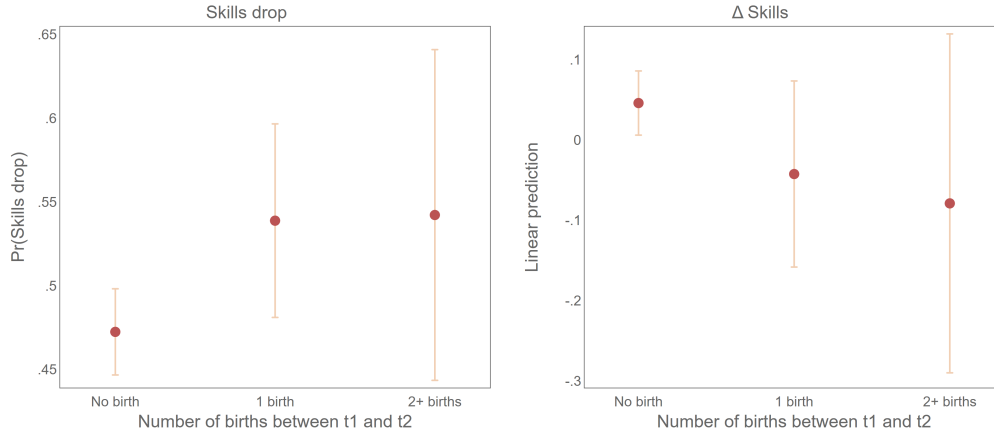
Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Skills t1	9796	.295	1.202	-4.23	5.555	.23
Skills t2	9796	.301	1.071	-4.269	5.485	.266
Skills drop	9796	.492	.5	0	1	0
Delta skills	9796	.006	.988	-4.6	4.589	.018
Birth between t1 and t2	9796	.141	.348	0	1	0
Leave duration (in months)	9268	1.319	5.837	0	92	0
Woman (yes/no)	9796	1.582	.493	1	2	2
Age at first birth	4814	29.506	4.878	18	51.1	29.5
Age at t1	9796	28.751	8.845	18.2	45	24.9
Age at t2	9658	35.1	9.167	24.1	54.2	30.9
Low education	9796	.015	.121	0	1	0
Medium education	9796	.714	.452	0	1	1
High education	9796	.271	.444	0	1	0
Delta education	9658	2.605	2.832	0	7	1
Number of children	9796	.984	1.217	0	12	0
No birth between t1 and t2	9796	.859	.348	0	1	1
1st birth between t1 and t2	9796	.061	.238	0	1	0
2nd birth between t1 and t2	9796	.049	.215	0	1	0
3rd+ birth between t1 and t2	9796	.032	.176	0	1	0
No birth between t1 and t2	9796	.859	.348	0	1	1
1 birth between t1 and t2	9796	.101	.301	0	1	0
2+ births between t1 and t2	9796	.041	.197	0	1	0
Migration background (yes/no)	9796	.057	.231	0	1	0
Mathematical skills	9796	.388	.487	0	1	0
Reading skills	9796	.462	.499	0	1	0
ICT skills	9796	.075	.263	0	1	0
Scientific skills	9796	.076	.264	0	1	0
SC5 (yes/no)	9796	.528	.499	0	1	1
Survey year t1	9796	2011.214	.74	2010	2013	2011
Survey year t2	9658	2017.346	1.71	2016	2022	2017
Time between birth and t2 (in months)	9658	68.535	21.976	1	114	71

Figure A.2: The effect of births on skill changes by birth rank



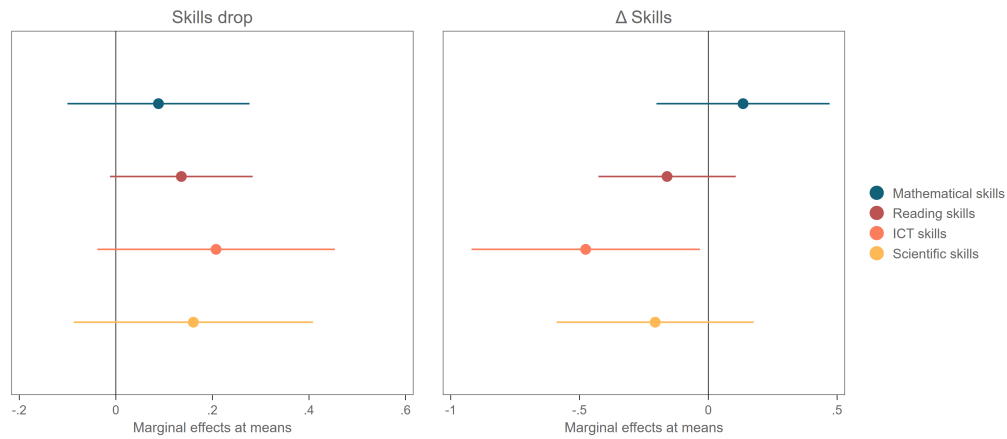
Note: The graph shows predictive margins with 95% confidence intervals for the probability that skills decrease between  $t_1$  and  $t_2$  based on Logit regressions (left panel) and the difference in skills between  $t_2$  and  $t_1$  based on OLS regressions (right panel). Control variables include gender, educational attainment, changes in educational attainment between  $t_2$  and  $t_1$ , age in 5-year-categories, the skill domain, the number of children, migration status, the time between the birth and  $t_2$ , the survey cohort, and the survey year at  $t_2$ . Weights are applied;  $N = 9,796$

Figure A.3: The effect of births on skill changes by the number of births



Note: The graph shows predictive margins with 95% confidence intervals for the probability that skills decrease between  $t_1$  and  $t_2$  based on Logit regressions (left panel) and the difference in skills between  $t_2$  and  $t_1$  based on OLS regressions (right panel). Control variables include gender, educational attainment, changes in educational attainment between  $t_2$  and  $t_1$ , age in 5-year-categories, the skill domain, the number of children, migration status, the survey cohort, and the survey year at  $t_2$ . Weights are applied;  $N = 9,796$

Figure A.4: The effect of births on skill changes by skill domain



Note: The graph shows marginal effects at means with 95% confidence intervals for the probability that childbirth between  $t_1$  and  $t_2$  decreases skills based on Logit regressions (left panel), and the difference in skills between  $t_2$  and  $t_1$  based on OLS regressions (right panel). Control variables include gender, educational attainment, changes in educational attainment between  $t_2$  and  $t_1$ , age in 5-year-categories, the number of children, migration status, the time between the birth and  $t_2$ , and the survey year at  $t_2$ . Weights are applied;  $N = 9,796$