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Cognitive Skills among Adults: An Impeding Factor for Gender Convergence?

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Abstract

For many different definitions of skills, higher qualifications relate to higher wages. In this paper, we investigate the gender skill gap in numeracy skills measured by standardized tests in the international PIAAC survey, with a special focus on its distributional characteristics. In line with the observed educational convergence, the skill gap is the lowest among the youngest cohorts. We investigate multiple factors that affect gender-specific skill levels and conclude that the field of study and being a parent are key explanatory factors for the lower skill levels of women. Additionally, women have lower returns to higher numeracy skills compared to similarly-skilled men. These findings explain part of the gender pay gap and point at mechanisms that create inequalities in the accumulation of skills. A better understanding of these mechanisms can help shaping policies to preserve human capital and address implicit gender discrimination.

Keywords: gender pay gap; skills; numeracy; PIAAC.

JEL Classifications: I24, J16, J24.

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1. Introduction

Gender differences in labour market outcomes and their determinants are a central topic in contemporary empirical economics. [Goldin \(2014\)](#) discusses how increased labour market participation of women, increasing educational equality of men and women, and lower occupational segregation across genders have led to a decrease of the unconditional gender pay gap in most rich countries over the last decades. She concludes that equalizing working conditions on the labour market in terms of time schedules and flexibility may abolish the remaining gender pay differences.

Our paper argues that – despite the increasing educational equality – there exist inequalities in skills among adult men and women, and these may impede the convergence of the gender pay gap. In particular, we provide empirical evidence on the gender-specific distributions of skills for different age groups and explore the driving factors along the skill distribution. We document how skill levels of men and women translate into gender differences in wages, and in particular, whether returns to skills differ for men and women, pointing at a discrimination pattern.

There is a large literature showing that better qualified adults – on average – earn higher wages. This relationship holds for various definitions of qualifications, such as higher educational levels ([Walker and Zhu, 2008](#)), additional on-the-job training ([Haelermans and Borghans, 2012](#)), and longer experience ([Altonji and Williams, 2005](#)), among others. Recently, skills as a more direct measure of qualifications have been added to this picture (see e.g., [Hanushek et al., 2015](#), who use PIAAC data). The richness of institutional settings in which skills are acquired poses a problem for the comparability of skill measures. In job hiring processes, skill-related features are evaluated as signals and are often complemented by specific entry tests or assessment centers to help compare skills of job candidates in a standardized way. On a broader scale, standardized skill tests for adults are usually not available, which is why empirical studies greatly rely on signals provided by (often self-reported) skill measures with highly restricted comparability. In this study, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC offers representative samples of respondents in more than 40 countries with standardized tests in three domains – numeracy, literacy, and problem-solving in technology-rich environments. We mainly focus on numeracy levels, as they have shown to be most predictive of individuals' wages ([Hanushek et al., 2015](#)).

We provide several novel insights into gender-specific skill levels and their relationship with wages. Firstly, we focus on the whole distribution of skills among women and men. Since gender-specific distributions of skills substantially overlap, focusing on mere average differences masks important heterogeneity within gender and, hence, may lead to an incomplete picture of the potentials of men and women in the labour market. Moreover, as the gender pay gap tends to be higher among high-earners, it is important to focus on that part of the distribution. Secondly, our analysis underlines that skill levels evolve after formal education is completed and are driven by a series of individual decisions as well as possible associated constraints. The gender-specific implications of the same decisions shed light on the channels for skill accumulation. These decisions not only affect the possible channels through which gender gaps in wages can be further diminished, but also imply potential long-term human capital losses for economies.

Using cross-sectional data from the PIAAC dataset, we are able to confirm the main finding from the literature that numeracy levels are predictive of wages to a higher extent than other skills and that they explain a substantial part of the gender pay gap. We can also show that numeracy skills play a role in wage progression, above the past wage levels, which also points at skills being an important deep parameter for wage formation. Furthermore, the returns to numeracy for men and women are, on average, not significantly different. However, when looking at a more nuanced picture - based on the differentiation between respondents with high vs. low numeracy levels - we find that returns to skills have gender-specific patterns. For men, belonging to the high-skilled group is associated with about 20 percent higher wages (than within the low-skilled group) for low-wage earners. This skill premium for men increases to up to 40 percent for the top earners. Among women, the returns to skills are nearly the same throughout all wage deciles, with returns to high skill levels being somewhat higher than for men among the low-wage earners, and being substantially lower than for men among the top earners. These findings are robust to the inclusion of controls for educational levels, fields of study, and occupations. A cautious interpretation of this result is that rewards to skills for women follow a different pattern than for men, potentially due to the existence of other gender-specific factors that outweigh the returns to skills and that are not observed in our data (e.g. effects of networks or differences in bargaining). More speculatively, it seems that there may be a lock-in effect of women in low-paying jobs, given by favoritism of women among the low-wage earners and their discrimination among the top earners.

We also study factors that may explain the different skill levels between men and women.

Exploiting the German panel extension of the PIAAC dataset, we show that young individuals up to the age of 45 gain skills over time whereas older individuals seem to experience skill depreciation. This trend can be observed for women aged 45-54 first whereas men in this age range still seem to improve their numeracy skills. Furthermore, we show that gender gaps in numeracy skills remain after controlling for past numeracy skills. We also document that the evolution of numeracy skills for men and women differs markedly around the arrival of a child, albeit with the limitations related to using cross-sectional data for this analysis. Similarly, the field of study being STEM or non-STEM can explain a large part of the difference in numeracy skills between men and women. We then show that labour-market conditions at age 15 do not seem to explain adult numeracy levels. It's rather parents' educational levels that play an important role in determining these decisions. Lastly, decomposing the numeracy gaps in an Oaxaca-Blinder framework for quantile analyses shows that a large part of the numeracy gap is unexplained and potentially is the result of differential returns to having children and educational levels. The small explained part can mainly be attributed to child care and respective fields of study.

The literature trying to grasp and explain gender differences in labour market outcomes has mostly focused on participation and wages as main outcomes. Only recently, a small but growing literature has started to look at cognitive skills and their relevance for other labour market outcomes. Since the release of PIAAC, a few studies have had a closer look at gender differences in adult skills. [Rebollo-Sanz and De la Rica \(2020\)](#) investigate gender differences in cognitive skills using the international PIAAC dataset, focusing on average differences. [Christl and Köppl-Turyna \(2020\)](#) use the Austrian PIAAC dataset to document gender differences in skills, tasks and skill matching of workers, and the impact of these factors on the gender wage gap using quantile regressions for their main empirical models. They estimate models similar to those of [Autor and Handel \(2013\)](#) and combine it with a decomposition method following [Chernozhukov et al. \(2013\)](#).

There is an older and larger literature investigating early-age gender differences in cognitive skills, and in numeracy skills in particular. [Hyde et al. \(2008\)](#) find gender differences across grades 2 to 11 in the US to be relatively small, whereas [Fryer and Levitt \(2010\)](#) find substantial differences emerging over the first six years of school. Similarly, [Contini et al. \(2017\)](#) document a large numeracy gap in favor of boys in Italy from grades two to ten, which is increasing in age. They also find gaps to be largest at the top of the test score distribution.

Likewise, [Robinson and Lubienski \(2011\)](#) use U.S. data to document that the gender gaps in math (favoring males) are largest at the upper end of the achievement distribution. [Ellison and Swanson \(2010\)](#) also find a gender gap favouring males at the far right tail of advanced mathematics, and conclude that many girls are not achieving their potential in math in most US high schools. More recently, [Autor et al. \(2020\)](#) find that gender differences in behavioral and academic outcomes are primarily driven by differences at both tails of the distribution. The effect of socio-economic status is stronger for boys, and it is an important driver of observed differences in schooling achievement, including differences in high-school dropouts. [Joensen and Nielsen \(2021\)](#) investigate the role of institutions and peer on gender differences in education choice.

Our objective to investigate gender skill differences across the wage distribution is motivated by the large literature documenting that gender differences in wages vary widely across the distribution and tend to be larger at the top (often referred to as the ‘glass ceiling’ effect). [Albrecht et al. \(2003\)](#) played a very important role in the diffusion of the concept of ‘glass ceilings’ in the context of gender differences in the labour market. They provide strong evidence that wage differences between men and women in Sweden in 1998 were larger at the top, and that this difference is not driven by characteristics they can control for. Similarly, [Collischon \(2019\)](#) documents a large glass-ceiling effect in Germany and [Arulampalam et al. \(2007\)](#) provide evidence for glass ceiling effects (as well as ‘sticky floor’ effects) across eleven European countries. They find that the gender wage gap widens at the top (and to some extent, the bottom) of the wage distribution. [Blau and Kahn \(2017\)](#) use data from the Panel Study of Income Dynamics (PSID) in the US to estimate gender wage gaps in the period 1980-2010. They find that the decrease in the gender wage gap is much slower at the top of the wage distribution and identify gender differences in occupations and industries as an important dimension. They briefly discuss gender differences in numeracy skills, and the possible role they may play for selection into STEM occupations. However, the numeracy skills they refer to only measure math test scores in high school. Furthermore, [Blau and Kahn \(2017\)](#) offer a very good overview of the methodologies behind calculating the glass ceiling. [Bertrand \(2018\)](#) reviews the recent literature exploring possible explanations of the glass ceiling effect across countries. For example, [Petrongolo and Ronchi \(2020\)](#) focus on the role of technological change and the rise of service jobs to explain labour market performances of men and women.

There is also previous work on the wage returns to skills for men and women, and on

the accumulation of skills over careers as well as the effects of career interruptions on earnings. Using the NLSY79, [Bacolod and Blum \(2010\)](#) present evidence that there has been an increase in the labour-market return to cognitive skills and a corresponding decrease in the return to motor skills. This has likely benefited women relative to men, since women tend to be more highly represented in occupations where cognitive skills are important while men are more likely to be in jobs that emphasize motor skills. We are able to enrich their discussion by investigating the role of numeracy skills in isolation, and painting a more nuanced picture than the (largely positive) one they discuss.¹ [Hanushek et al. \(2015\)](#) investigate the returns to cognitive skills using PIAAC data, and document that returns to cognitive skills are insignificantly different for males and females in the group of countries they look at. This again stresses the importance of studying gender differences in skills more in depth, in order to reconcile the evidence from the glass ceiling literature with the lack of differential average returns to cognitive skills between men and women.

2. Data

Our main data source is the Programme for the International Assessment of Adult Competencies (PIAAC), a survey of adult skills developed by the OECD. The PIAAC study delivers internationally comparable measures of adult competencies, similarly to what the PISA study does with 15-year-olds. The study focuses on cognitive skills required to advance at work and participate in society, with the main focus on numeracy³ and literacy⁴ skills. Additionally, some of the participating countries conducted tests on problem solving in technology-rich environments.⁵ The measurement of skills is based on assessments, i.e. tests including a series

¹This literature is in turn related to a slightly older literature on the role of work interruptions on skill depreciation. [Edin and Gustavsson \(2008\)](#) use administrative data to investigate the role of work interruptions on subsequent wages, and find that depreciation of general skills is ‘economically important’. Perhaps surprisingly, they do not look at differential effects by gender. [Skans and Liljeberg \(2014\)](#) investigate how non-thematic subsidised career breaks in Sweden affect future wages of participants (compared to rejected applicants).² [Albrecht et al. \(2018\)](#) use Swedish administrative data to investigate the careers of women and men born in the years 1960–70 who completed a university degree in Business or Economics. By focusing on a relatively homogeneous group of individuals, they address many of the possible selection problems that affect other studies. They find wage growth to be lower among women.

³Numeracy 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*. A numeracy test can include understanding of a time series on birth rates or understanding different temperature measurement scales.

⁴Literacy 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*. For instance, a test on literacy includes a list of pre-school rules and a question on their comprehension.

⁵Sample questions can be found at <https://www.oecd.org/skills/piaac/samplequestionsandquestionnaire.htm>, last accessed on February 9, 2021.

of questions for each particular domain. Each skill is measured on a 500-point scale.⁶ In this paper, we mostly focus on numeracy skills since they have shown to be the most relevant in predicting wages (Hanushek et al., 2015) and are likely to be more comparable across countries.

In addition to the skill measures, PIAAC gathers information on a wide set of socio-economic characteristics and labour market covariates of the individuals. In particular, it includes educational attainment and field of study, current work status, occupation, wages and working time, labour market history etc. The richness of background information is an important advantage of this dataset that allows for a thorough analysis of the factors that are at interplay with an individual’s skills.⁷ The survey initially ran in August 2011 – March 2012 in the OECD countries. In its second round (April 2014–March 2015), PIAAC was conducted in nine additional countries, including new OECD members and some non-OECD countries.⁸ In our study, we mostly use information on the 32 countries that provide information on skill levels and wages. Table B.1 lists the countries entering our analysis and the sample sizes at our disposal. As we do not focus on international comparisons, we standardize the test scores in each country to have a mean of zero and a variance equal to one (see also Data Appendix A).

We acknowledge that the cross-sectional nature of our data source poses a major restriction on the empirical analysis, as we cannot observe the accumulation process of skills within individuals. To the best of our knowledge, the only country that used the initial sampling of PIAAC for a longitudinal study was Germany. The resulting PIAAC-L dataset provides a unique setting to follow individuals and their skills over time, but has two main disadvantages: First, samples sizes unfortunately are too small to conduct thorough analyses of individuals characteristics. Second, the time span covered by the dataset only comprises of three years (from 2012 to 2015) which limits the variation in skill development that can be observed. Nonetheless, we use this extension for some selected additional analyses that provide some useful insights into skills accumulation, keeping in mind that these findings cannot necessarily be generalized to other countries of the international PIAAC study.

⁶It is important to underline that the test scores measure crystallized intelligence in particular domains and cannot be interpreted as ability or the overall level of intelligence (Halpern, 2013). It is also important to keep in mind that – despite the overall goal of the PIAAC tests to reduce country or gender biases to a minimum – even the testing mode itself and particular questions may contain undetected bias (Schroeders et al., 2016).

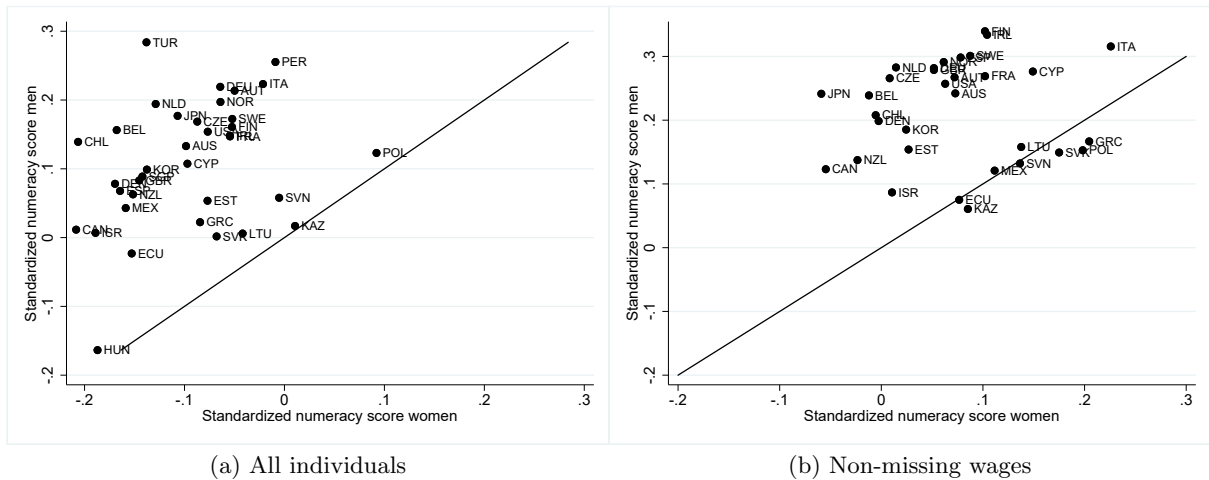
⁷For a more detailed description of the variables used in the analysis see Data Appendix A.

⁸The full list of participating countries and the survey schedule can be found at <https://www.oecd.org/skills/piaac/>.

3. Numeracy skills of men and women

We begin by showing some cross-country evidence to provide an insight on the similarities of gender skill gaps within the sample. We then present a few general characteristics of numeracy skills that will be helpful in interpreting the results from the empirical analyses. Figure 1 is a scatter plot of standardized numeracy scores by country, with each data point referring to the average score of men (y axis) and women (x axis) in each country. In this figure, we differentiate between (a) all individuals and (b) those with non-missing wages, since this paper includes joint analyses of wages and numeracy levels. Both graphs contain a 45-degree line, where test scores would lie in case of their equality between genders within country. Strikingly, in all countries in the overall PIAAC sample, men on average have higher numeracy scores than women such that the resulting data cloud entirely lies above the 45-degree line (Figure 1 (a)). In the subsample with non-missing wages (Figure 1 (b)), a handful of countries exhibits average gender parity in skills, whereas the majority of countries exhibits higher numeracy skills scores among men. For comparison purposes, Figures B.1 and B.2 in our Appendix depict equivalent data clouds for literacy and problem solving. The figures reveal that gender disparity in literacy is much less pronounced and that there is a range of countries where women have higher literacy scores than men. Scores for problem solving resemble more the distribution of numeracy scores: the data cloud is located further away from the 45-degree parity line and there are only three countries where women score better than men in this domain.

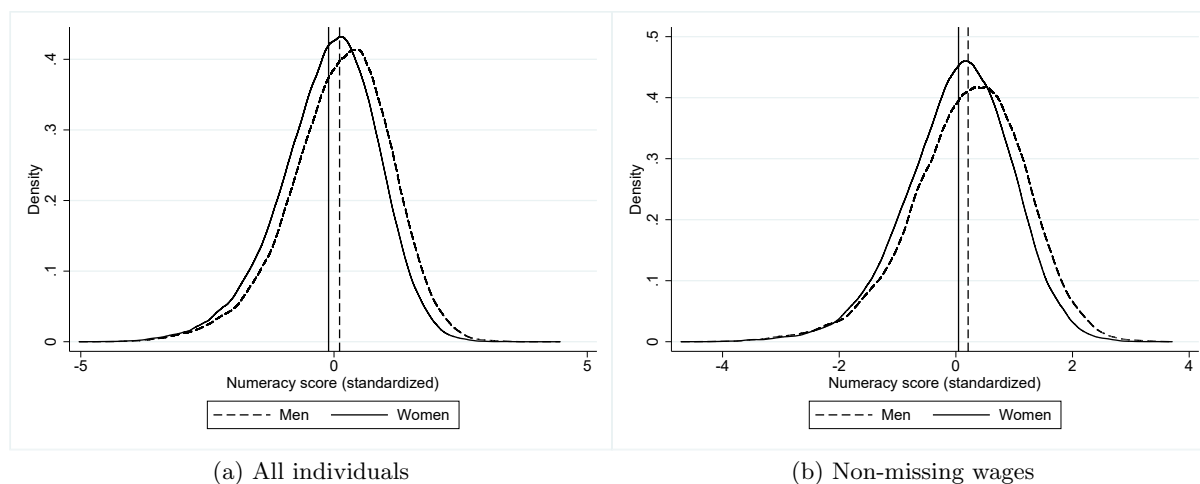
Figure 1: Gender-specific numeracy scores by country



Notes: Standardized numeracy scores for men and women aged 20-65 by country. Standardization uses individuals' sampling probability. The graph additionally includes the 45-degree line to depict potential equality of test scores. Sample contains all individuals with non-missing numeracy scores. Data source: PIAAC international PUF 2012.

Focusing only on mean test scores may lead to an incomplete picture of the advantage of men in numeracy. In fact, Figure 2 (a) and Figure 2 (b) show that the distributions of numeracy scores of men and women across countries overlap substantially, implying higher heterogeneity of test scores within gender than between men and women. Figure B.3 depicts the gender-specific distributions of literacy and problem solving scores, revealing that gender similarity in literacy is the highest, with an almost perfect overlap of the literacy score distributions of men and women.

Figure 2: Numeracy score distributions of men and women



Notes: Standardized numeracy scores for men and women aged 20-65. Standardization uses individuals' sampling probability. Vertical lines represent the respective means for women and men. Sample contains all individuals with non-missing numeracy scores. Data source: PIAAC international PUF 2012.

In the following analysis, we often divide numeracy skills into two categories: above the country-specific median and below. Table 1 shows some descriptive statistics of men and women with “low numeracy” (defined as being below the country-specific median) and “high numeracy” (above the country-specific median). We present descriptive statistics both for all survey participants (first four columns), as well as those with non-missing wages (rlast four columns).

The share of men in the low-numeracy group is 45 percent, whereas it is 9 percentage points higher in the high-numeracy group. The shares of younger age groups (20 to 29 and 30 to 44) are higher among the high-numeracy group, but the distribution of ages groups does not show a distinctive gender pattern. The share of respondents living with their spouses is fairly evenly distributed between the two numeracy levels and genders. A more distinctive pattern can be seen for respondents having children. In the low-numeracy group, 68 percent of men and 79 percent of women have children, whereas in the high-numeracy group the share of

Table 1: Sample description by gender and numeracy level

	All participants				Non-missing wages			
	Low numeracy		High numeracy		Low numeracy		High numeracy	
	Men	Women	Men	Women	Men	Women	Men	Women
Share	0.45	0.55	0.54	0.46	0.48	0.52	0.55	0.45
<i>Socio-demographics</i>								
Aged 20-29	0.19	0.17	0.25	0.26	0.22	0.18	0.23	0.24
Aged 30-44	0.30	0.31	0.39	0.39	0.35	0.35	0.44	0.43
Aged 45-54	0.24	0.24	0.21	0.21	0.26	0.28	0.22	0.23
Aged 55-65	0.26	0.27	0.15	0.15	0.18	0.19	0.11	0.10
Live with spouse/partner	0.74	0.74	0.75	0.72	0.75	0.73	0.79	0.74
Has children	0.68	0.79	0.62	0.68	0.67	0.76	0.64	0.66
<i>Education</i>								
Lower secondary or less	0.36	0.35	0.12	0.10	0.29	0.22	0.09	0.06
Upper/post-secondary	0.49	0.44	0.45	0.40	0.54	0.49	0.44	0.37
Tertiary	0.15	0.21	0.43	0.50	0.17	0.28	0.47	0.58
<i>Field of study</i>								
General programmes	0.12	0.14	0.14	0.15	0.12	0.14	0.11	0.12
Teacher training and educ. science	0.02	0.06	0.03	0.10	0.02	0.08	0.04	0.12
Humanities, languages and arts	0.03	0.05	0.05	0.09	0.03	0.06	0.05	0.09
Social sciences, business and law	0.07	0.13	0.16	0.23	0.08	0.17	0.17	0.26
Science, mathematics and computing	0.04	0.03	0.11	0.08	0.04	0.04	0.11	0.08
Engineering, manufact. and constr.	0.27	0.05	0.31	0.07	0.32	0.05	0.33	0.07
Agriculture and veterinary	0.04	0.02	0.03	0.02	0.03	0.02	0.03	0.02
Health and welfare	0.02	0.10	0.03	0.11	0.02	0.15	0.03	0.14
Services	0.06	0.09	0.04	0.06	0.07	0.10	0.05	0.06
Field of study STEM	0.31	0.08	0.42	0.15	0.36	0.09	0.45	0.15
<i>Occupation</i>								
Armed forces occupations	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00
Managers	0.06	0.04	0.13	0.08	0.04	0.03	0.11	0.07
Professionals	0.07	0.14	0.23	0.31	0.07	0.15	0.23	0.32
Technicians and associate professionals	0.10	0.13	0.17	0.19	0.11	0.14	0.18	0.19
Clerical support workers	0.05	0.12	0.06	0.14	0.06	0.14	0.07	0.15
Service and sales workers	0.14	0.31	0.10	0.19	0.13	0.31	0.10	0.17
Skilled agric., forestry & fishery workers	0.06	0.02	0.03	0.01	0.03	0.01	0.01	0.00
Craft and related trades workers	0.24	0.04	0.15	0.02	0.24	0.03	0.14	0.02
Plant and machine operators/assemblers	0.17	0.04	0.09	0.02	0.19	0.04	0.09	0.02
Elementary occupations	0.11	0.15	0.04	0.05	0.12	0.15	0.05	0.05
<i>Labor Market</i>								
Share employed	0.73	0.57	0.83	0.72	1.00	1.00	1.00	1.00
Share full-time employed	0.90	0.72	0.91	0.77	0.92	0.73	0.93	0.79
Average wage	2.44	2.37	2.71	2.57	2.44	2.37	2.71	2.57
Wage p10	1.53	1.48	1.78	1.68	1.53	1.48	1.78	1.68
Wage p90	3.20	3.13	3.52	3.35	3.20	3.13	3.52	3.35

Notes: Descriptive statistics for men and women aged 20-65 by numeracy levels above or below the median, using sampling weights. Numeracy medians calculated by country. Field of study STEM refers to categories "Science, mathematics and computing" and "Engineering, manufacturing and construction". Data source: PIAAC international PUF 2012.

respondents with children is 6 percentage points lower for men and even 11 percentage points lower for women. This may partly be due to the fact that older respondents are over represented in the low-numeracy group. As expected, lower education levels are more frequent among the low-numeracy group. In both numeracy-level groups, women have a higher frequency of tertiary education than men which is in line with the recent literature on women surpassing men on this dimension. For many fields of study, we document relative gender parity, with some exceptions: in both numeracy groups, men study engineering, manufacturing and construction much more frequently than women, who particularly dominate in social sciences, business and law, as well as health and welfare. Studying social sciences, business and law, as well as science, mathematics and computing is much more frequently associated with higher numeracy levels for both genders. Among men and women with lower numeracy scores, STEM fields of study are less frequent than among the high-numeracy group. Also, in both numeracy groups, women choose a STEM field of study less often. As for occupations, the most frequent ones in the low-numeracy group are craft and related trades workers for men and service and sales workers for women. In the high-numeracy group, men and women belong most frequently to the occupation group of professionals. The share of employed grows from the low- to the high-numeracy group both for men (from 73 to 83 percent) and especially for women (from 57 to 72 percent). Among these, the share of full-time workers is around 90 percent among men in both skill groups whereas it is much lower among women (72 percent in the low-numeracy group and 77 percent in the high-numeracy group). The average wage grows with numeracy levels for both genders, although the raw wage gap is much higher in the high-numeracy group. Looking at wage percentiles, we observe that the pay gap is widening with numeracy levels and is especially high among high-numeracy top earners. In general, these descriptive statistics show that numeracy levels are closely linked to labour market activity, wages, the probability of having children, and some fields of study and occupations.

4. Numeracy and wages

Our focus on numeracy skills is grounded in their relevance in the labour market. Next, we discuss wage returns to skills.

4.1. *Average returns to skills*

Figure B.4 in our Appendix shows the distributions of (log) hourly wages of men and women pooled across all countries (adjusted by country-specific PPP). The two distributions substantially overlap, with an almost perfect overlap for the low tails of the distributions, and a widening gap at log wages of about 1.7. The latter can be explained by women being over-proportionately engaged in part-time work which – besides leading to lower monthly earnings because of reduced working hours – is also related to a penalty in hourly wage rates.

In the following, we explore how skills and wages relate, and what insights skill gaps can provide on the formation of the gender pay gap. Because of the cross-sectional nature of the data, we observe skills and wages simultaneously. Their relationship is likely to be bi-causal: individuals with higher skills tend to have better-paying jobs, but at the same time a better-paying job most likely requires more practice of particular skills and thus helps in preserving skill levels. Table 2 illustrates how wages and test scores correlate on average. In line with the previous literature (Hanushek et al., 2015) we find that numeracy levels have a higher predictive power to wages than literacy or problem solving skills, both when included individually as well as simultaneously. Additionally, this table includes interactions of the respective skill variables with a dummy for being female, showing that *average* returns to skills for men and women are statistically indistinguishable for numeracy and literacy skills in the specifications where skills enter separately (Columns 3 and 5). This is not the case for problem-solving where returns to skills are higher for women (Column 7). This preserves into the specification where all skills are included simultaneously (Column 8), although it has to be kept in mind that only a subset of countries assessed problem-solving skills. In this reduced sample, we can also observe a negative additional return to numeracy for women, which was not visible when including numeracy skills only.

4.2. *Inter-temporal wage patterns*

Interestingly, numeracy skill levels do not only explain current wages, but also matter for the evolution of wages over time. Table 3 exploits the panel structure of the German PIAAC-L data by showing the dependence of wages in 2015 on wages and numeracy skills in 2012. Column (1) confirms the existence of a gender pay gap in wages 2015 after controlling for age, education, field of study, occupational groups and full-time work in 2012. Column (2) reveals

Table 2: Returns to skills: regression of log hourly wages on skill scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.180*** (0.004)	-0.166*** (0.004)	-0.166*** (0.004)	-0.176*** (0.004)	-0.176*** (0.004)	-0.168*** (0.005)	-0.170*** (0.005)	-0.159*** (0.005)
Numeracy (Num.)		0.068*** (0.002)	0.070*** (0.003)					0.058*** (0.007)
Num. * Female			-0.004 (0.004)					-0.025** (0.009)
Literacy (Lit.)				0.057*** (0.002)	0.057*** (0.003)			0.018** (0.007)
Lit. * Female					-0.001 (0.004)			0.008 (0.009)
Problem Solving (PS)						0.049*** (0.002)	0.041*** (0.003)	-0.006 (0.005)
PS * Female							0.016*** (0.004)	0.027*** (0.007)
Age groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full-time indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102576	102567	102567	102567	102567	74524	74524	74524
R^2	0.604	0.611	0.611	0.609	0.609	0.606	0.606	0.609

Notes: Dependent Variable: log trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Skill measures are standardized at the country level using sampling probabilities. Least squares regression with country fixed effects, weighted by individual sampling probability. Dummies for education, field of study and occupation as well as a full-time indicator are included in all columns. Baseline category for age groups is 20-29, the constant is omitted in the output. Sample contains all individuals aged 20-65 with non-missing data for wages as well as the respective controls. Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent. Data source: PIAAC international PUF 2012.

a high positive dependence of wages in 2015 from wages three years before and shows that the female dummy indicating the gender pay gap even loses significance, which reveals that past wages absorb factors driving the gender pay gap. Moreover, the interaction of past wages with the female dummy is small and negative, indicating that wage evolution over the observed three years was, on average, gender neutral. Column (3) shows the positive dependence of wages in 2015 from past numeracy levels. As expected, the correlation is smaller than with past wages, whereas the interaction with the female dummy is larger but still statistically insignificant. Most interestingly, column (4) shows that numeracy skills in 2012 have explanatory power for wages in 2015 beyond what can be explained by past wages. This highlights the importance to look at the emergence and development of numeracy skills beyond their importance for wage gaps. Column (5) additionally includes contemporaneous numeracy levels for men and women, which both remain insignificant in the presence of past numeracy and wages. However, especially the last column shows that past numeracy for men is correlated with an additional wage premium, which is completely cancelled out for women. This finding implies that higher numeracy levels

are associated with higher wage growth, but only for men.⁹

Table 3: Dependence of wages in 2015 on wages in 2012 and numeracy skills

	(1)	(2)	(3)	(4)	(5)
Female	-0.071** (0.027)	0.019 (0.129)	-0.043 (0.029)	-0.041 (0.126)	-0.026 (0.126)
Wages (2012)		0.508*** (0.040)		0.482*** (0.039)	0.481*** (0.039)
Wages (2012) × Female		-0.012 (0.046)		0.017 (0.046)	0.013 (0.046)
Numeracy (2012)			0.103*** (0.020)	0.066*** (0.019)	0.062** (0.021)
Numeracy (2012) × Female			-0.051 (0.028)	-0.045 (0.024)	-0.061* (0.028)
Numeracy (2015)					0.007 (0.017)
Numeracy (2015) × Female					0.025 (0.026)
Age groups 2012	Yes	Yes	Yes	Yes	Yes
Educational categories 2012	Yes	Yes	Yes	Yes	Yes
Field of study 2012	Yes	Yes	Yes	Yes	Yes
Occupational categories 2012	Yes	Yes	Yes	Yes	Yes
Full-time indicator 2012	Yes	Yes	Yes	Yes	Yes
Observations	1734	1734	1734	1734	1734
R^2	0.321	0.526	0.341	0.534	0.535

Notes: Dependent variable: log trimmed gross hourly wages in 2015. Least squares regression weighted by individuals' sampling probability. Dummies for education, field of study and occupation as well as a full-time indicator are included in all columns. Baseline category for age groups is 20-29, the constant is omitted in the output. Sample contains individuals aged 20-65 and employed in 2012 and 2015 with non-missing data for wages, skill measures, gender, and all respective controls (in 2012). Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent. Data source: PIAAC-L Germany 2015 and 2012.

Another way to see the importance of numeracy skills for gender differences in wages is to look at their contribution to explaining gender wage gaps. Figure B.5 (A) depicts the result of an Oaxaca-Blinder decomposition of the gender pay gap into the explained and unexplained parts without considering numeracy levels (left bar) and with additional controls for numeracy skills (right bar). It shows that, on average, numeracy levels contribute positively and substantially to the gender gap formation, whereas average returns to numeracy - as mentioned above - do not differ by gender and, thus, do not contribute to the gender pay gap. Figure B.5 (B) performs the same decomposition by country and shows that considering numeracy levels lowers the gender pay gap only in few countries (among which are Japan, Chile and Czech Republic), whereas they are a substantial factor for explaining gender pay gaps in most other countries in our sample. Again, returns to numeracy do not show a substantial contribution to the average gender pay gap in most countries.

⁹All presented specifications are robust to the exclusion of particular controls.

4.3. Distributional analyses of numeracy skills and wages

Average differences mask important heterogeneity in the gender-specific patterns of skills and wages. We therefore now turn to analysing the distributional aspects of numeracy gaps between women and men. Figure 3 plots both the share of women as well as average numeracy scores for women and men along hourly wage deciles in the pooled sample of all countries with wage information. We can see that the share of women monotonically decreases along the wage distribution: from about 60 percent in the first decile to less than 35 percent in the top decile (dotted line). The numeracy levels for both genders also show an almost perfect monotonicity, with numeracy levels being, on average, lower for low-wage earners and higher for high-wage earners. However, this simple representation reveals an interesting gender-specific pattern: men (dashed line) have relatively higher numeracy levels at the bottom and at the top of the wage distribution, whereas the numeracy levels around the median wage are virtually the same as those of women (solid line). Within the wage deciles, the distribution of skills is very compact (see the p10-p90 intervals in Figure 3), which points at a close relationship between numeracy levels and wages, i.e. numeracy being a good predictor for the wage level.

Figure 3: Numeracy scores along the wage distribution



Notes: (Weighted) Shares of females within the respective deciles of hourly wages and standardized numeracy scores for men and women. Standardization uses individuals' sampling probability, deciles are calculated by country. Sample contains all individuals with non-missing wages. Data source: PIAAC international PUF 2012.

But even the same numeracy levels can have differential returns along the wage distribution for men and women. In order to elicit this aspect, we perform a decomposition based on the re-centered influence function (RIF) as suggested by [Firpo et al. \(2009\)](#). For this purpose, we estimate the following regression specification:

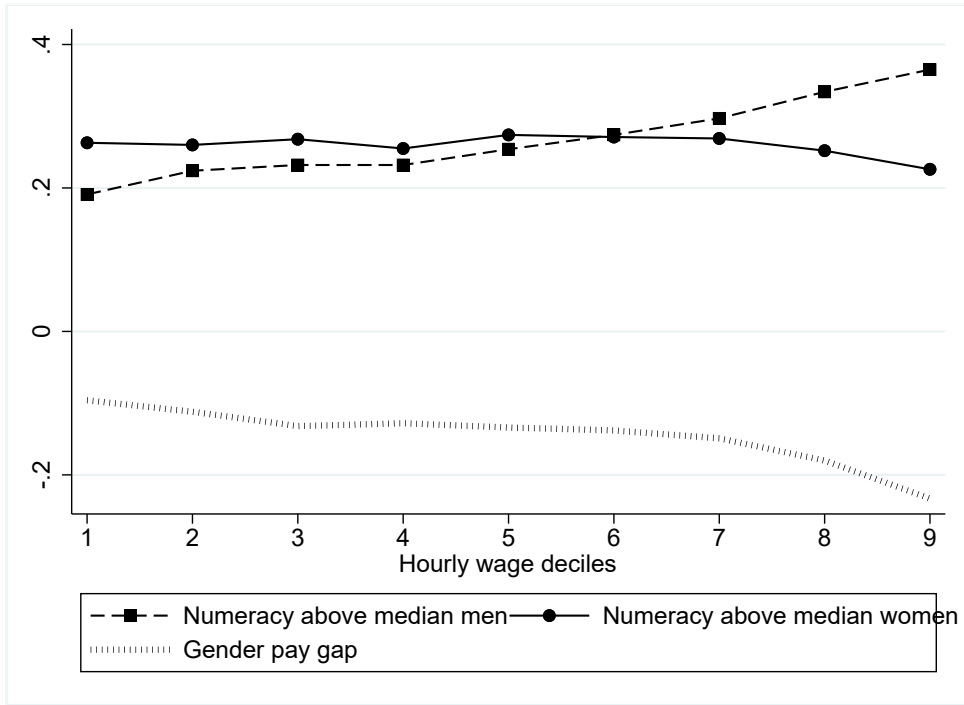
$$\log(W_{ic}) = \alpha + \beta * \text{Female}_{ic} + \gamma NS_{ic}^{\text{top50}} + \delta NS_{ic}^{\text{top50}} * \text{Female}_{ic} + \mathbb{X}_{ic}\mu + e_c + \epsilon_{ic} \quad (1)$$

The dependent variable is the log hourly wage of an individual i living in country c . *Female* is a binary variable equal to 1 for female respondents and zero otherwise. NS_{ic}^{top50} indicates that a respondent's numeracy skill level is above the median in his/her country of residence (skill levels below the median are the base category). We also include an interaction term of the female dummy and the numeracy level. Thus, $\hat{\gamma}$ captures the returns to having above-median numeracy skills for men, relative to those with below-median numeracy levels. $\hat{\delta}$ captures the additional returns from above-median numeracy levels for women, compared to men. In our basic specification, we only control for a set of dummies for age groups 30 to 44, 45 to 54 and 55 to 65 (with ages 20-29 as the reference category) and control for the country of residence. In further analyses presented in the appendix we add more controls. We then estimate equation 1 at all nine decile borders. For illustrative purposes, we summarize the estimation results in [Figure 4](#), which depicts the relative returns to numeracy levels for men ($\hat{\gamma}$) and for women ($\hat{\gamma} + \hat{\delta}$). The figure also depicts the marginal effect for females ($\hat{\beta} + \hat{\delta}$) to depict the gender pay gap at the respective decile.

[Figure 4](#) confirms the established empirical fact that the gender pay gap is increasing (i.e. worsening) from the bottom to the top of the wage distribution and is especially pronounced at the top two deciles. The figure also reveals gender-specific patterns in returns to numeracy: below the median hourly wage, the returns to high numeracy levels are slightly higher for women than for men. In the middle of the wage distribution, the returns to numeracy are about equal and for the top two deciles, returns to higher numeracy levels are much higher for men than for women. This comes from the fact that returns to higher numeracy skills for women remain stable over the wage distribution and slightly decrease for very high numeracy levels whereas men see an increase of their returns to above-median numeracy skills that is especially pronounced in the highest deciles.¹⁰

¹⁰[Figure B.6](#) depicts the returns to numeracy for women relative to men by plotting the $\hat{\delta}$ stemming from a country-wise estimation of equation 1. With few exceptions, we observe a dominant pattern of returns to

Figure 4: Returns to numeracy levels, by gender



Notes: Plot of the coefficients presented in equation 1 corresponding to unconditional quantile regressions without further controls (only age groups and country fixed effects) at each wage decile border. Graphs represent relative returns to numeracy levels for men ($\hat{\gamma}$, dashed lines with squares) and for women ($\hat{\gamma} + \hat{\delta}$, solid lines with circles) as described above. The dotted line plots the marginal effect for females ($\hat{\beta} + \hat{\delta}$) as described above. Corresponding coefficients can be found in table B.2. Numeracy scores are standardized using individuals' sampling probability. Sample contains all individuals aged 20-65 with non-missing wages and numeracy scores. Data source: PIAAC international PUF 2012.

Figure B.7 provides the same graph resulting from an estimation of Equation 1 with additional controls for (A) education levels and the field of study, (B) occupational categories, and (C) a full-time indicator. We observe that the general picture of gender-specific returns to numeracy among the top earners remains unchanged in all specifications. This gender-specific detachment of skill levels from wages of top earners suggests that the existence of a glass ceiling in wages is less related to skills themselves, but rather other factors related to skills that we cannot observe (e.g. networks) that then in turn hinder skilled women from earning more. Furthermore, relatively higher returns to skills for women in the lower wage deciles may point at lock-in effects of women with high skill levels in the low-wage segments.

To show gender-specific patterns of full-time employment as well the influence of children, in Table B.6 we add an indicator for having children as well as its interaction with the female dummy. We observe positive returns to children for men that increase from the lower to the numeracy for women being higher for lower wages and decreasing with wage levels, so that above-median numeracy skills pay off less for women than for men among high-earners.

upper deciles of the wage distribution. For women, this positive return is entirely cancelled out. This points at distinctively different wage settings for fathers and mothers, even after controlling for their education, occupation and working time schedule.

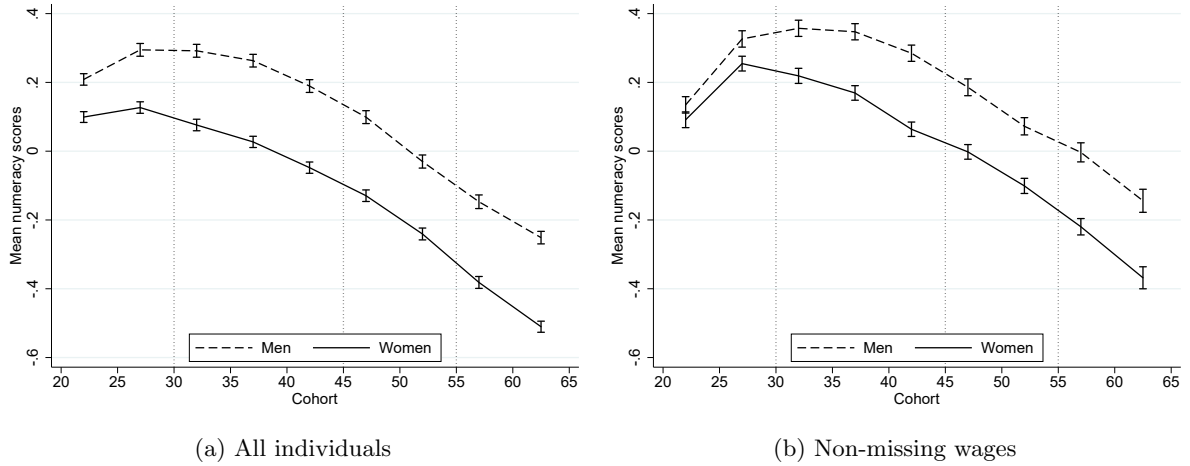
5. Drivers of skill differences between women and men

The evidence presented above reveals that women have a wage disadvantage resulting from both lower numeracy levels as well as lower returns to numeracy skills, especially at the top of the wage distribution. Hence, the question emerges whether these differences in numeracy levels as well as returns can be explained by current or past choices that women have made compared to men. In the following, we provide empirical evidence on some of the channels that may explain the differences in observed numeracy levels. These differences are to a large extent an outcome of a series of past events and decisions of the respondents (which may, in turn, be highly selective on numeracy levels).

Depicting the average numeracy levels for men and women in 5-year age groups (Figure 5, (a) for all individuals, (b) for those with non-missing wages) is an illustrative point of departure. Within all age groups, the mean numeracy scores are higher for men than for women, with the lowest gap for the youngest group, which is especially striking among respondents with non-missing wages. Moreover, for women numeracy scores peak at age 25-30 and then decrease. Men's numeracy levels are also highest for ages 25-30, but then remain at about the same level for the age groups 30-35 and 35-40 before they equivalently decrease for older groups. Hence, gender differences in numeracy skills are not specific to any age range but instead are present across the entire age distribution.

Figure B.8 provides gender-specific numeracy test scores for different age groups by country and confirms that younger cohorts tend to have higher test scores and that for them the male-female scatters are also located closer to the 45-degree line, pointing at higher skill equality. As these figures rely on cross-sectional data stemming from respondents of different ages, they cannot be interpreted as a development of skills over the life course. The documented pattern could be driven both by a cohort component (e.g. more engagement in science for women from younger cohorts) and a life cycle component (e.g. gender-specific skill depreciation with age). In particular, a dominant life cycle component may imply that the relatively more equal gender distribution of skills among the young can be annihilated over the course of their lives

Figure 5: Numeracy scores, by age and gender



Notes: Mean standardized numeracy scores by age (in 5-year intervals) for men and women aged 20-65. Confidence intervals for each data point are added, vertical lines represent cutoffs of age groups used in the regressions at ages 30, 45, and 55. Standardization uses individuals' sampling probability. Sample contains all individuals with non-missing numeracy scores and age. Data source: PIAAC international PUF 2012.

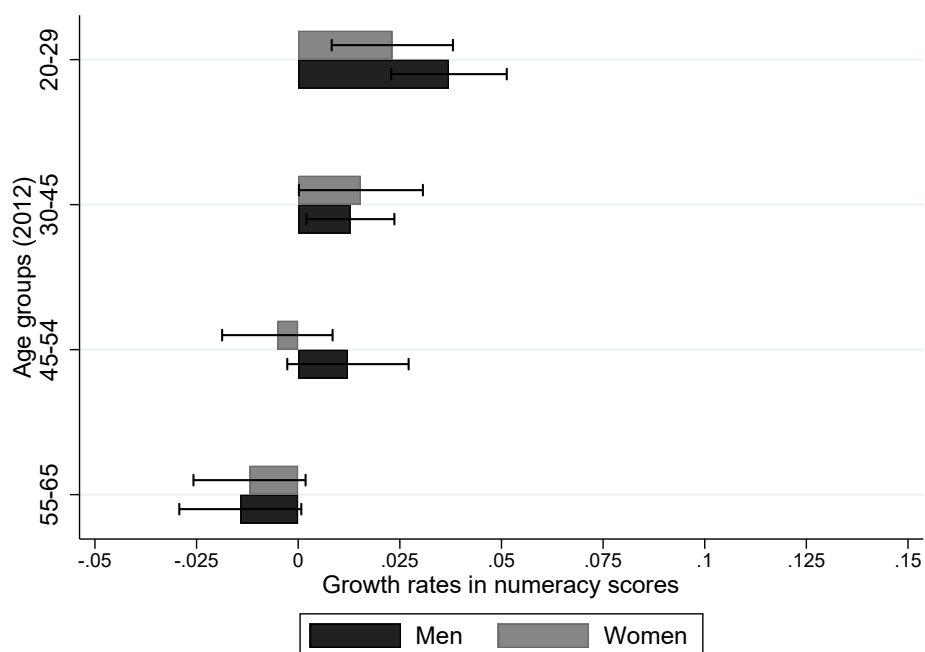
if institutional settings for skill accumulation and depreciation do not change.

5.1. Short-term accumulation of skills using panel data

Using the German panel dataset PIAAC-L we are able to disentangle these two effects, although with a smaller national sample and a rather short time span. [Rebollo-Sanz and De la Rica \(2020\)](#) mention that age-related gender skill profiles are likely to depend on the over-time skill depreciation. With the PIAAC-L data, we are able to empirically test if skills depreciate over time. Figure 6 shows the changes in skill levels for both genders by age groups. Among the youngest age group in 2012 (20-29 years old), both men and women improve their numeracy skills over time (i.e. until 2015). Men's skill gains are higher than those of women, though not significantly different. In the age group 30-45, both men and women improve their numeracy skills by about the same amount, the improvement is smaller than in the youngest age group though. In the age group 45-54, women have an insignificant skill loss, whereas men again improve their skills. Among the oldest group aged 55 to 65, we observe a (statistically insignificant) skill loss for both men and women.

Figures [B.9](#) and [B.10](#) depict the average growth in numeracy scores by gender for further categories. Men across all numeracy quartiles except the highest one experience skill growth over time (Figure [B.9](#) (A)). Strikingly, the largest growth of numeracy score is detected in the lowest numeracy quartile. Moreover, for women this is the only decile where we document growth.

Figure 6: Difference in numeracy scores between 2015 and 2012 for women and men, by age (Germany only)



Notes: Growth rates in numeracy scores for men and women in Germany between 2015 and 2012 by age groups. Growth rates are calculated by dividing the difference between 2015 and 2012 numeracy scores by 2012 numeracy scores. Age groups refer to the age reported in 2012. Confidence intervals are added for bar. Sample contains all individuals aged 20-65 with non-missing numeracy scores in 2012 and 2015, and age in 2012 (2,961 observations). Data source: PIAAC-L German SUF 2015 and 2012.

We also find similar over-time numeracy growth for men and women without children and with one child, but not for respondents with two children where women seem to lose numeracy skills (Figure B.9 (B)). In line with numeracy growth being an attribute of young respondents, we find the largest numeracy growth for men in the lowest education category (Figure B.9 (C)). Among the different fields of study, we observe pronounced over-time numeracy growth among women in science, mathematics and computing (Figure B.10 (A)). Among 1-digit ISCO occupations, there are only three clear patterns (Figure B.10 (B)): men in elementary occupations gain numeracy skills over time whereas women in this category experience numeracy skill losses. Furthermore, men in the category of professionals gain numeracy skills over time whereas women experience skill growth only among the group of sales and service workers. The employment status of individuals is also related to numeracy skill growth (Figure B.10 (C)): men in both full-time and part-time employment on average gain numeracy skills whereas women only seem to gain when out of employment. The latter might be driven by women in education. This evidence suggests that the phase of educational attainment is crucial to numeracy accumulation, but

that on-the-job skill accumulation is present only among men.

Table 4 depicts the dependence of the current numeracy levels from past numeracy skills for men and women. We observe a gender gap in current numeracy skills, even after controlling for past numeracy, although the interaction term of past numeracy with the female dummy remains insignificant. The addition of various controls shows that the accumulation of numeracy barely changes when including the field of study (potentially, because it is a past decision), but is more affected by the inclusion of the current occupation and an indicator for full-time employment. Strikingly, the inclusion of the dummy variable of having children and its interaction with the female dummy implies that children affect skill accumulation of women, but not of men. In this last specification (column 6), the coefficient on the female dummy decreases substantially in size and loses significance.

Table 4: Accumulation of numeracy skills over time

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.110**	-0.113***	-0.129***	-0.143**	-0.164***	-0.086
	(0.034)	(0.034)	(0.039)	(0.046)	(0.048)	(0.065)
Numeracy (2012)	0.750***	0.716***	0.696***	0.644***	0.643***	0.644***
	(0.029)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
Numeracy (2012) × Female	-0.045	-0.044	-0.034	0.007	0.011	0.002
	(0.040)	(0.039)	(0.039)	(0.042)	(0.043)	(0.043)
Children						-0.000
						(0.053)
Children × Female						-0.117
						(0.077)
Age groups 2012	Yes	Yes	Yes	Yes	Yes	Yes
Educational categories 2012	No	Yes	Yes	Yes	Yes	Yes
Field of study 2012	No	No	Yes	Yes	Yes	Yes
Occupational categories 2012	No	No	No	Yes	Yes	Yes
Full-time 2012	No	No	No	No	Yes	Yes
Observations	2961	2960	2956	2353	2347	2347
R^2	0.502	0.507	0.514	0.487	0.488	0.489

Notes: Dependent variable: numeracy scores in 2015. Least squares regression weighted by individuals' sampling probability in 2015. Sample contains individuals with non-missing numeracy scores in 2015 and 2012 as well as the respective controls, the constant is omitted in the output. Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent. Data source: PIAAC-L German SUF 2015 and 2012.

5.2. Heterogeneity by parental status

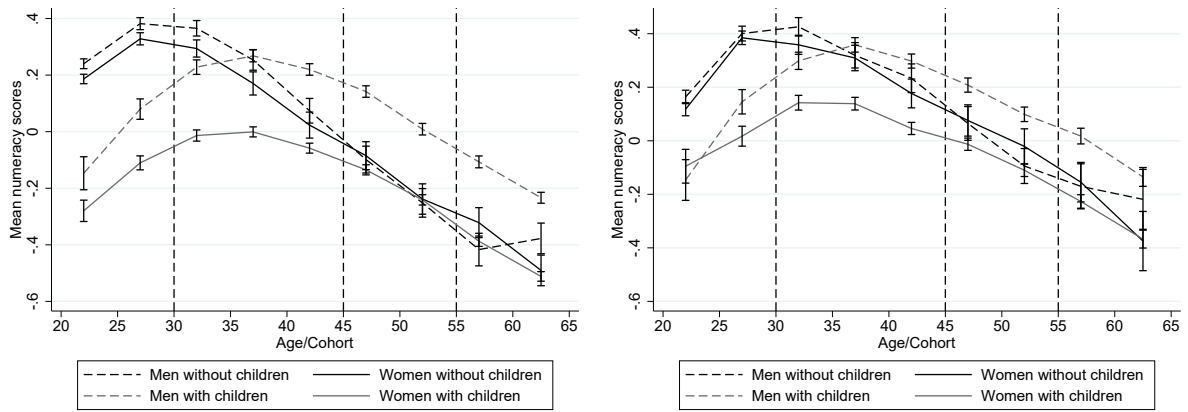
As was suggested by Table B.6, parental status plays an important role for the gender-specific relationship between skills and wages. Figure 7 (A) replicates the numeracy score profiles over age/cohort for men and women with and without children (for all individuals on the left, and

for those with non-missing wages on the right). Strikingly, the numeracy profiles for men and women without children are almost overlapping for all age/cohort groups, whereas the gender gap for men and women with children is substantial and widening with age/cohort. Profiles for men and women with children exhibit lower numeracy scores for ages/cohorts below 35, which may be explained by selection into relatively early parenthood. For individuals aged above 35, the numeracy skills of men are substantially higher than those of all other groups, whereas the numeracy skills of women tend to be same as for the group of men and women without children. Figure 7 (B) presents returns to numeracy skills and the gender pay gap along the wage distribution by parental status. For childless men and women (black lines), the gender gap is much lower, and the returns to numeracy are constant, with minor exemptions for the first and the last decile borders. For men with children (gray lines), we observe increasing returns to numeracy over wage deciles, whereas the skill returns of women with children are slightly declining above the median. Together, this suggest a stronger favoritism with respect to skills of fathers as compared to mothers.

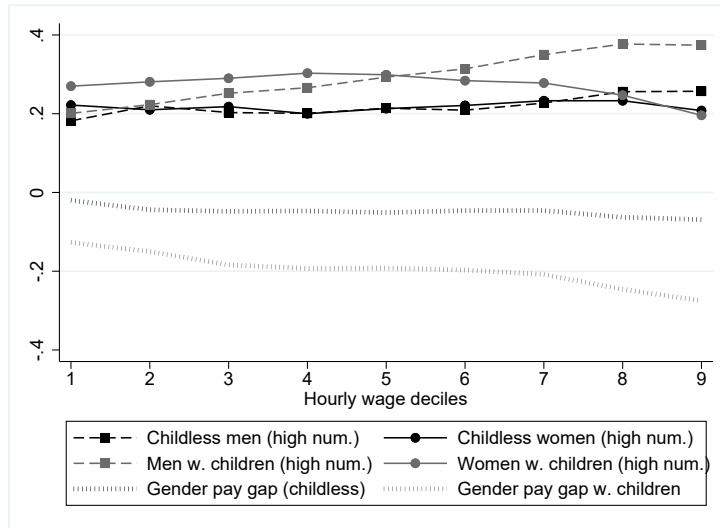
Figure 7 may partly be driven by selectivity into parental status. In order to address this aspect, Figure B.11 (A) presents gender-specific numeracy profiles for men and women at the age at which they had their first child. It illustrates that especially women who had their first child at young ages, show lower numeracy levels than men who had their first children at the same age, and also as women who had their first children later in life. Figure B.11 (B) shows the residual numeracy levels remaining after controlling for educational levels, which shows an even higher discrepancy by gender and high selectivity on numeracy levels for fertility decisions.

In a longitudinal framework, it would be possible to study the role of children in an event study. With cross-sectional data, this is not feasible as we cannot observe the same individuals before and after the first childbirth. But an approximation to this event study representation is possible. Figure 8 presents the numeracy profiles of men and women centered around the country- and gender-specific average age at first childbirth (represented by the solid vertical line at zero). To the left of this line, we plot numeracy levels of childless respondents, who have not reached the respective average age at first childbirth in their country. To the right of this solid vertical line, we plot numeracy levels of parents with children aged 0 to 6 (up to the vertical dashed line) and parents of older children (to the right of the vertical dashed line). In this approximation to an event study design, we observe that numeracy levels of men and women before childbirth show a small gap, whereas for those with children we see a much wider

Figure 7: Parental status, numeracy levels and wages



(a) All individuals (b) Non-missing wages
 (A) Numeracy levels over cohorts, by gender and parental status

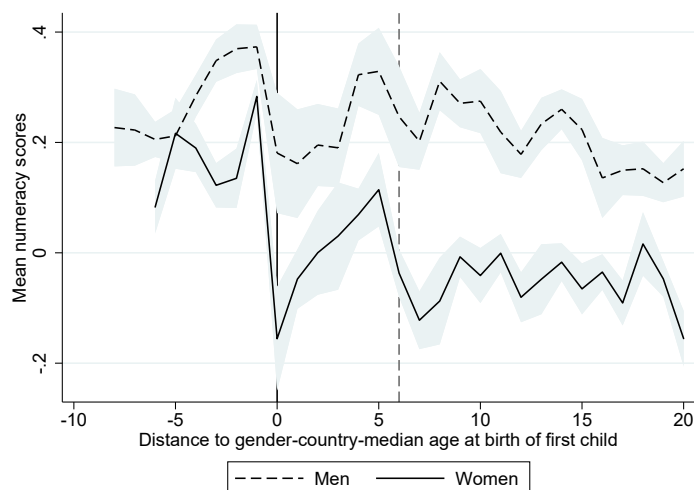


(B) Returns to skills, by gender and parental status

Notes: Panel (A): Mean standardized numeracy scores by age (in 5-year intervals) for men and women with and without children. Confidence intervals for each data point are added, vertical lines represent cutoffs of age groups used in the regressions at age 30, 45, and 55. Standardization uses individuals' sampling probability. Sample contains all employed individuals aged 20-65 with non-missing numeracy scores, age, and child information. Panel (B): Relative returns to above-median numeracy levels for men and women by having children. The dotted lines plot the marginal effect for females. Corresponding coefficients can be found in tables B.7 and B.8. Numeracy scores are standardized using individuals' sampling probability. Sample contains all individuals aged 20-65 with non-missing wages, numeracy scores and information on children. Data source: PIAAC international PUF 2012.

gap. In the actual event-study, this would indicate a widening of the numeracy gap after the first childbirth. In our case, it surely masks some selection into parenthood, but it still provides suggestive evidence of a similar channel as for the wage child penalty. Figure B.12 (A) replicates this for numeracy levels of the employed only, which yields a lower increase in the numeracy gap after child birth- This can be explained by high selectivity of the woman into the labour force after the median country-gender-specific age at first child birth (Figure B.12 (B)).

Figure 8: Numeracy levels by gender around the age of first birth



Notes: Mean standardized numeracy scores by distance to the country-gender-specific age at birth of the first child for men and women with children (positive distance) and without children (negative distance). Confidence bands are added, vertical lines represent cutoffs for individuals with and without children (solid line at 0) and children's ages for individuals with children (dashed line at 6). Individuals with children aged 0-5 form the group with distances 0-5, equivalently for children aged 6 or above. Sample contains all individuals aged 20-65 with non-missing numeracy scores, age, and child information. Data source: PIAAC international PUF 2012.

5.3. Heterogeneity by STEM occupations

Given that numeracy levels are especially required in STEM-related occupations, we provide heterogeneity analysis by STEM versus non-STEM fields of study (Figure 9) and industries (Figure B.13), both differentiate between all individuals and those with non-missing wages. In line with our expectations, Figure 9 (A) shows that men and women in STEM-related fields of study have higher numeracy levels than men and women in other fields of study. For the youngest cohorts in STEM, women have even slightly higher skills levels, whereas the skill gap in favor of men is present for age groups 35-40 and older. Figure 9 (B) depicts the gender pay gap and the returns to skills along the wage distribution. The gender pay gap for respondents educated in STEM-related fields of study is constant over the wage distribution whereas it increases with

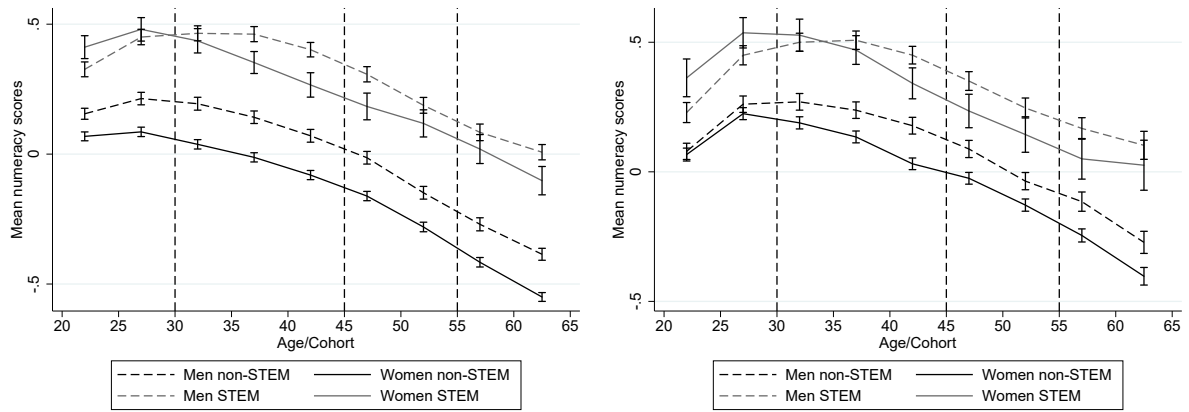
higher wages for non-STEM fields of study as found before. Strikingly, we observe that women with education in STEM-related fields have substantially higher returns to their skills among lower wage deciles, pointing towards higher favoritism of women at the bottom of the wage distribution.

Figure B.13 addresses the potential differences in numeracy levels for respondents in STEM/non-STEM industries, depending on their field of study. For respondents educated in fields of study related to STEM, Figure B.13 (A) shows that the numeracy profiles for men and women in STEM and non-STEM industries almost overlap. For the respondents educated in non-STEM fields of study, Figure B.13 (B) also depicts an overlap of profiles of women in STEM and non-STEM industries. At the same time, in this subfigure, numeracy levels of men are higher in STEM and (especially) non-STEM industries. The latter evidence may point at selection of STEM-educated men into non-STEM industries, though a further exploration is beyond the scope of this paper. For our purposes, we conclude that the choice of the field of study (as shown in Figure 9) is decisive for numeracy levels, not the current occupation in a particular industry.

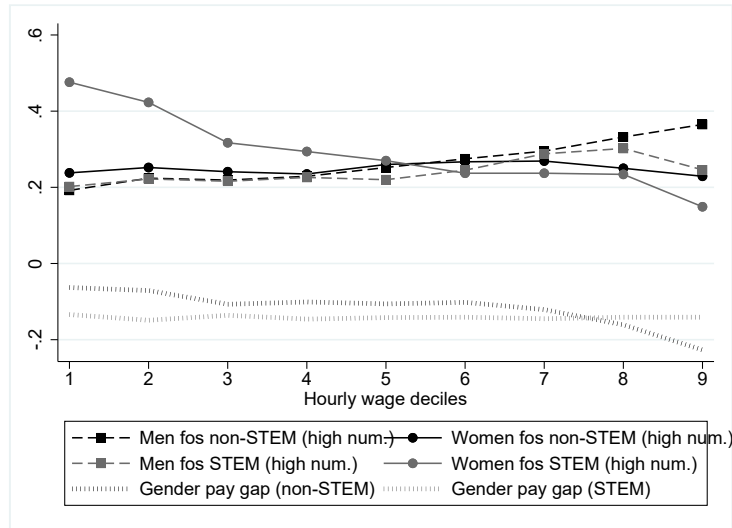
5.4. *Country-specific institutions*

The literature emphasizes that gender differences in cognitive abilities may already emerge in school (Kahn and Ginther, 2017). It is also recognized that overall conditions during the time of initial labour market entry are important for the educational levels and the employment trajectory (Arellano-Bover, 2020; Hampf et al., 2020). Additionally, country norms regarding the role of women for child care can matter for the labour market outcomes. Figure B.14 plots the country averages for the gender numeracy gap and the child penalty in numeracy scores calculated using the PIAAC data by country against the percentage of the ISSP-respondents who agree with the statement that ‘mothers of children under school age should stay at home’. Although this country-level analysis reveals some correlation between norms and labour market outcomes, it appears crucial to use the variance available in the data *within* countries to study these relationships. In the following, we re-estimate the gender gap in numeracy adding various controls for the influences and conditions that individuals in our sample faced when they were 15 years old, i.e. at an age where a young individual would start thinking about their plans for the future. Table 5 starts with the specification in column (1) that includes only the female dummy, thus estimating a raw gender gap for all the individuals in the sample with

Figure 9: STEM v non-STEM field of study, numeracy levels and wages



(a) All individuals (b) Non-missing wages
 (A) Numeracy levels over cohorts, by gender and field of study



(B) Returns to skills, by gender and field of study

Notes: Panel (A): Mean standardized numeracy scores by age (in 5-year intervals) for men and women with STEM/non-STEM fields of study. Confidence intervals for each data point are added, vertical lines represent cutoffs of age groups used in the regressions at age 30, 45, and 55. Standardization uses individuals' sampling probability. Sample contains all employed individuals with non-missing numeracy scores, age, and field of study. Panel (B): Relative returns to above-median numeracy levels for men and women by field of study. The dotted lines plot marginal effect for females respectively. Corresponding coefficients can be found in tables B.9 and B.10. Numeracy scores are standardized using individuals' sampling probability. Sample contains all individuals with non-missing wages, numeracy scores and field of study. Data source: PIAAC international PUF 2012.

non-missing numeracy scores and not being first-generation migrants (for whom we cannot adequately control for the country-of-origin institutional conditions). The average raw gender gap in numeracy in this sample is -0.210. Inclusion of age brackets as controls yields nearly the same result. Specification (3) adds the country-specific unemployment rate in the year the respondent was 15 and its interaction with the female dummy, to control for the overall economic conditions in the country at that time. We see a significant positive correlation of the unemployment rate with the numeracy level for women, but no large change in the gender numeracy gap (calculated as the marginal effect in the last row of the table). Specification (4) adds the labour force participation (LFP) rates for men and women at age 15 as well as their interactions with the female dummy. The LFPs and the unemployment rate as a variable mix show differential influence on men and women and their inclusion increases the gender numeracy gap by about one percentage point (see last row of the table). Specification (5) includes a proxy for *females in science* that measures the aggregate share of female authors in astrophysics in a country in the years when the respondent was 14 to 16 years old.¹¹ Although this proxy appears reasonable to be included in such context as it aims to depict the presence of female role models in science, its inclusion does not significantly correlate with numeracy levels in the presence of other controls, nor does it contribute to the gender numeracy gap. Column (6) adds parental education levels and their interaction with the female dummy to control for the influence of the family environment. In the presence of other controls, we observe that parental education strongly correlates with the numeracy levels, though the interaction terms show no significant difference by gender. Column (7) includes the set of variables on parental education and interactions of the country and year of birth of the respondents to control for all possible institutional factors that may vary by country and year. Compared to specification (1), we document a slight reduction in the numeracy gap by less than one percentage point (see last row). Overall, this evidence points to a relatively small importance of the institutional factors for the formation of the gender numeracy gap.

5.5. *Decomposition of numeracy gaps*

In order to understand how the characteristics presented in table 1 contribute to the formation of the gender gap in numeracy, we perform an Oaxaca-type decomposition of an estimated

¹¹The choice of astronomy as a field relates to the availability of reliable data from specialized scientific libraries in STEM for many countries and a possibly long period of time. The data stems from <http://ads.harvard.edu>.

Table 5: Influence of initial labour market conditions on numeracy scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.210*** (0.008)	-0.211*** (0.008)	-0.268*** (0.018)	-0.012 (0.165)	0.280 (0.352)	0.297 (0.349)	-0.210*** (0.014)
Unemployment rate			0.077 (0.235)	0.376 (0.311)	0.184 (0.373)	0.096 (0.360)	
Unemployment rate × Female			0.703*** (0.197)	0.400 (0.283)	0.360 (0.368)	0.145 (0.360)	
Female LFP				0.229 (0.259)	0.385 (0.341)	0.423 (0.338)	
Female LFP × Female				0.237* (0.115)	0.318* (0.162)	0.263 (0.162)	
Male LFP				0.001 (0.399)	-0.146 (0.502)	-0.606 (0.522)	
Male LFP × Female				-0.508* (0.218)	-0.944* (0.449)	-0.936* (0.443)	
Females in science					0.242 (0.283)	0.261 (0.275)	
Females in science × Female					-0.137 (0.307)	0.028 (0.301)	
Mother educ. intermediary						0.226*** (0.022)	0.196*** (0.015)
Mother educ. intermediary × Female						0.046 (0.029)	0.064** (0.019)
Mother educ. high						0.419*** (0.027)	0.420*** (0.018)
Mother educ. high × Female						0.048 (0.036)	0.029 (0.024)
Father educ. intermediary						0.209*** (0.022)	0.219*** (0.015)
Father educ. intermediary × Female						-0.018 (0.030)	-0.025 (0.020)
Father educ. high						0.489*** (0.026)	0.467*** (0.018)
Father educ. high × Female						-0.062 (0.035)	-0.061** (0.024)
Aged 30-44		-0.012 (0.030)	-0.016 (0.032)	0.032 (0.037)	0.054 (0.042)	0.028 (0.038)	0.010 (0.049)
Aged 45-54		-0.070 (0.072)	0.017 (0.104)	0.246 (0.154)	0.302 (0.169)	0.504** (0.159)	0.086 (0.140)
Aged 55-65		-0.675*** (0.157)	-0.574*** (0.145)	0.077 (0.179)	0.118 (0.182)	0.507** (0.173)	0.132 (0.115)
Observations	88666	88666	78871	60282	37001	34687	82445
Gender numeracy gap	-0.210	-0.211	-0.215	-0.227	-0.228	-0.221	-0.202

Notes: Dependent Variable: standardized numeracy scores. Least squares regression with country fixed effects as well as dummies for the year in which individuals were 15 years old, weighted by individual sampling probability. Column 7 additionally adds country-times-year15 fixed effects. Estimation sample excludes all observations with missing numeracy score and first generation migrants. Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent. Results look similar when just considering countries with earnings information or only individuals with non-missing wages (results available upon request). Data source: PIAAC international PUF 2012.

unconditional quantile regression, as suggested by [Firpo et al. \(2009\)](#). In particular, we first estimate the following unconditional quantile regression:

$$NS_{ic} = \alpha + \mathbb{X}_{ic}\mu + e_c + \epsilon_{ic}, \quad (2)$$

where NS_{ic} denotes the standardized numeracy score of an individual i from country c , \mathbb{X}_{ic} comprises the individual-level characteristics from Table 1: socio-demographics (four age groups and being a parent), educational groups (3 categories: primary, secondary, tertiary), fields of

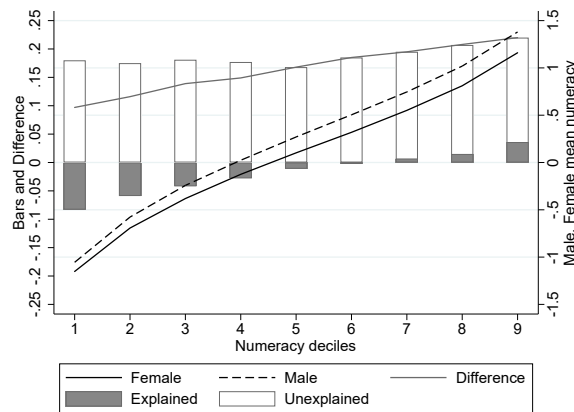
study, and current occupation. Here, e_c denotes a country dummy that we include in the equation to control for the differences in the labour market institutions between countries. We estimate Equation 2 separately for men and women, and perform the Oaxaca-Blinder-style decomposition into the gender differences in numeracy levels explained by the observed characteristics captured in \mathbb{X}_{ic} and the unexplained part, given by the differences in the returns to these characteristics by gender μ .

Figure 10 (A) presents the numeracy levels of men and women by decile (legend on the right axis), their difference and its decomposition into the explained and unexplained parts (legend on the left axis). The figure documents that the numeracy gap slightly opens with increasing numeracy levels. The explained part (i.e. based on observed characteristics) actually contributes negatively to the differences in numeracy levels below the median and only enters positively at the top of the numeracy distribution. Overall, however, the unexplained part dominates, especially above the median.

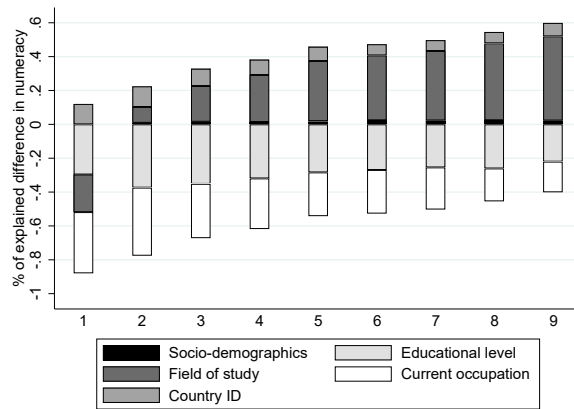
Figure 10 (B) shows the percentage contribution of the broad categories of controls (socio-demographics, educational level, field of study, occupation, country dummy) to the numeracy gap formation. Figure B.15 contains a detailed decomposition of the explained part of the numeracy gap by socio-demographics, field of study, and occupation. Figure 10 (C) presents the unexplained part of the gap associated with the same variable groups, whereas Figure B.16 provides details on the decomposition of the unexplained part by socio-demographics, field of study, and occupation. Figure 10 (B) reveals that women tend to have educational levels and occupations that are associated with higher numeracy levels and, hence, these factors contribute negatively to the numeracy gap. At the same time, their choice of field of study contributes positively to the gap and is a factor whose importance increases with the numeracy level (with the largest contribution of Engineering, Manufacturing and Construction, see Figure B.15 (B)). In sum, occupations explain a small proportion of the gap, but a closer look reveals that belonging to the group of Managers as well as to Craft and related workers increases the gender numeracy gap, whereas belonging to Professionals decreases it (see Figure B.15 (C)). The country dummy that captures institutional differences, contributes positively to the gender gap in numeracy.

The largest contributors to the unexplained part of the gap (Figure 10 (C)) are returns to socio-demographics and educational levels (that both increase the gap), as well as to the field of study that decreases the gap. When looking at the detailed decomposition (Figure B.16),

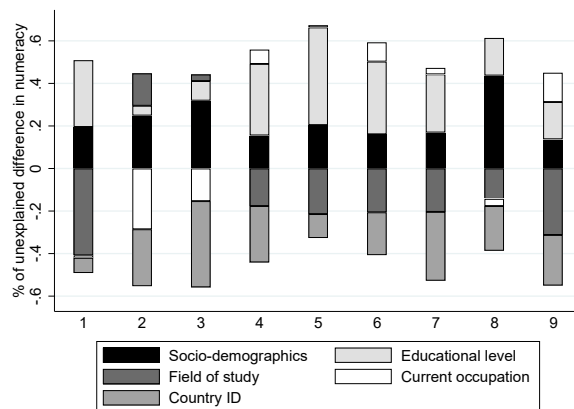
Figure 10: Oaxaca-style decomposition of the factors contributing to numeracy scores



(A) Numeracy scores by decile: Explained vs. unexplained by observed characteristics



(B) Explained



(C) Unexplained

Notes: Oaxaca-Blinder type decomposition of gender numeracy gaps by numeracy decile for employed individuals aged 20-65 using the command *oaxaca_rif*. Explanatory variables used: age groups, children, education, field of study, occupation, and country dummies. Results look similar when just considering countries with earnings information or only individuals with non-missing wages for the explained part and differ slightly for the unexplained part (results available upon request). Data source: PIAAC international PUF 2012.

we see that returns to having children and being in the occupation groups of Professionals and Craft and Related Trade Workers are all related to relatively lower numeracy levels for women, whereas studying Engineering, Manufacturing and Construction is related to higher numeracy levels for women.

Overall, we conclude that the observed characteristics of women, and especially their low presence in STEM-related fields of study is associated with a higher gender numeracy gap. Women are over-proportionately present among professionals, which contributes negatively to the numeracy gap, but within this group they have lower numeracy levels. The presence of children is related to a substantial part of the numeracy gap.

6. Conclusion

This paper investigates gender-specific patterns in skills, their driving factors, and their relation to gaps in wages with a particular focus on distributional aspects. We use direct skill measures from the PIAAC data to study this relationship, hereby focusing on numeracy skills since they have shown to be particularly predictive to wages. Using PIAAC gives us the advantage of an objective skill measure for adults, i.e. a deeper insight at the contemporaneous levels of skills in contrast to past educational levels that are often used in the literature. At the same time, the contemporaneous nature of our skill measures means that they are both input factors for current and future skill levels and wages, as well as outcomes from past education, life events, as well as the institutional context that accompanies skill accumulation.

We first study the relationship of numeracy levels with wages and document that, on average, higher skills translate into higher wages. This also holds when studying the longitudinal data from the German PIAAC-L where higher numeracy levels also relate to higher wage growth. However, the described relationship of numeracy and wages is much weaker for women than for men. Looking at the numeracy levels along the wage distribution reveals that numeracy levels of men exceed those of women at the bottom and especially at the top of the wage distribution. Using an unconditional quantile regression, we show that returns to numeracy are almost the same for women along the wage distribution, whereas they are increasing for men. This finding also holds when controlling for education, field of study, occupation, and children. This suggests that the absence of progressive returns to skills for women may be a factor impeding them from aspiring and preserving higher numeracy levels in the long run.

Indeed, the numeracy levels of men of women are lower for younger cohorts and higher for the older ones, which may both be driven by different initial levels of numeracy at young ages and the influence of various events during the life course. Although we acknowledge that our main data source is unable to detect longitudinal changes due to its cross-sectional nature, we are able to empirically detect two driving factors of particular importance. First, we document that having children makes a distinctive difference for the numeracy levels of men and women. For childless men and women, the skill-cohort profiles and returns to skills along the wage distribution almost overlap, which is not true for mothers and fathers. The numeracy levels become more unequal at typical ages for the birth of the first child and do not substantially converge when children are getting older. Second, we detect that being educated in STEM-related fields of study is related to higher numeracy levels both of men and women. However, we also document that the returns to numeracy are particularly high for women with education in STEM in the low-wage sector, which points to a profound discrimination pattern. When comparing education in STEM and being employed in a STEM industry, we unsurprisingly conclude that education in STEM is more important for numeracy levels than the current job industry. Concerning the country-level institutional factors, we do not find a strong impact on the gender numeracy gap. The decomposition of numeracy levels along its distribution confirms that the gender gap in numeracy is particularly dependent on the field of study.

Overall, our results imply that numeracy skills are an important driver for wages that is not stable over time and can accumulate or depreciate depending for example of labour market participation and family responsibilities. Therefore, our results support the importance of measures towards increasing numeracy levels of women by promoting STEM fields of study, but also underline that maintenance of numeracy levels and measures against its depreciation are of particular importance to women, especially for mothers. Our results also point at undesirable patterns with respect to the returns to skills: favoritism of numeracy skills of women among low-wage earners and discrimination of their numeracy skills among top-earners. Hidden factors like these may additionally discourage women from gaining and maintaining higher numeracy levels.

Finally we would like to acknowledge the importance of data on objective skill measures among adults that help to delve into the human capital stock in detail. Availability of better longitudinal data could offer valuable insights in human capital depreciation, especially when the number of observations allows to study skill profiles around importance events in life, such

as child birth, labour market entrance, on-the-job training, among others.

References

- Albrecht, J., Bjorklund, A., and Vroman, S. (2003). Is There a Glass Ceiling in Sweden? *Journal of Labor Economics*, 21(1):145–177.
- Albrecht, J., Bronson, M. A., Thoursie, P. S., and Vroman, S. (2018). The career dynamics of high-skilled women and men: Evidence from Sweden. *European Economic Review*, 105(C):83–102.
- Altonji, J. G. and Williams, N. (2005). Do wages rise with job seniority? a reassessment. *ilr Review*, 58(3):370–397.
- Arellano-Bover, J. (2020). The Effect of Labor Market Conditions at Entry on Workers’ Long-Term Skills. IZA Discussion Papers 13129, Institute of Labor Economics (IZA).
- Arulampalam, W., Booth, A. L., and Bryan, M. L. (2007). Is There a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wage Distribution. *ILR Review*, 60(2):163–186.
- Autor, D., Figlio, D. N., Karbownik, K., Roth, J., and Wasserman, M. (2020). Males at the Tails: How Socioeconomic Status Shapes the Gender Gap. NBER Working Papers 27196, National Bureau of Economic Research, Inc.
- Autor, D. H. and Handel, M. J. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, 31(S1):59–96.
- Bacolod, M. P. and Blum, B. S. (2010). Two sides of the same coin: U.s. ”residual” inequality and the gender gap. *The Journal of Human Resources*, 45(1):197–242.
- Bertrand, M. (2018). Coase Lecture – The Glass Ceiling. *Economica*, 85(338):205–231.
- Blau, F. D. and Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, 55(3):789–865.
- Chernozhukov, V., Fernández-Val, I., and Melly, B. (2013). Inference on Counterfactual Distributions. *Econometrica*, 81(6):2205–2268.
- Christl, M. and 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.
- Collischon, M. (2019). Is There a Glass Ceiling over Germany? *German Economic Review*, 20(4):329–359.
- Contini, D., Tommaso, M. L. D., and Mendolia, S. (2017). The gender gap in mathematics achievement: Evidence from Italian data. *Economics of Education Review*, 58(C):32–42.
- Edin, P.-A. and Gustavsson, M. (2008). Time out of work and skill depreciation. *ILR Review*, 61(2):163–180.
- Ellison, G. and Swanson, A. (2010). The Gender Gap in Secondary School Mathematics at High Achievement Levels: Evidence from the American Mathematics Competitions. *Journal of Economic Perspectives*, 24(2):109–128.
- Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3):953–973.
- Fryer, R. G. and Levitt, S. D. (2010). An Empirical Analysis of the Gender Gap in Mathematics. *American Economic Journal: Applied Economics*, 2(2):210–240.

- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119.
- Haelermans, C. and Borghans, L. (2012). Wage effects of on-the-job training: A meta-analysis. *British Journal of Industrial Relations*, 50(3):502–528.
- Halpern, D. F. (2013). *Sex differences in cognitive abilities*. Psychology press.
- Hampf, F., Piopiunik, M., and Wiederhold, S. (2020). The Effects of Graduating from High School in a Recession: College Investments, Skill Formation, and Labor-Market Outcomes. CESifo Working Paper Series 8252, CESifo.
- Hanushek, E. A., Schwerdt, G., Wiederhold, S., and Woessmann, L. (2015). Returns to skills around the world: Evidence from piaac. *European Economic Review*, 73:103–130.
- Hotchkiss, J. L., Pitts, M. M., and Walker, M. B. (2017). Impact of first birth career interruption on earnings: evidence from administrative data. *Applied Economics*, 49(35):3509–3522.
- Hyde, J. S., Lindberg, S. M., Linn, M. C., Ellis, A. B., and Williams, C. C. (2008). Gender similarities characterize math performance. *Science*, 321(5888):494–495.
- Joensen, J. S. and Nielsen, H. S. (2021). Gender convergence in education choice: The role of institutions and peers. Available at SSRN: <https://ssrn.com/abstract=3246074>.
- Kahn, S. and Ginther, D. (2017). Women and STEM. NBER Working Papers 23525, National Bureau of Economic Research, Inc.
- Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimüller, J. (2019). Child penalties across countries: Evidence and explanations. In *AEA Papers and Proceedings*, volume 109, pages 122–26.
- OECD (2016a). *The survey of adult skills: Reader’s companion*. OECD Publishing.
- OECD (2016b). Technical report of the survey of adult skills (piaac), second edition.
- Ortego-Martí, V. (2017). Differences in skill loss during unemployment across industries and occupations. *Economics Letters*, 161(C):31–33.
- Petrongolo, B. and Ronchi, M. (2020). Gender gaps and the structure of local labor markets. *Labour Economics*, 64(C).
- Rebollo-Sanz, Y. F. and De la Rica, S. (2020). Gender gaps in skills and labor market outcomes: evidence from the piaac. *Review of Economics of the Household*, pages 1–39.
- Robinson, J. P. and Lubienski, S. T. (2011). The development of gender achievement gaps in mathematics and reading during elementary and middle school: Examining direct cognitive assessments and teacher ratings. *American Educational Research Journal*, 48(2):268–302.
- Schroeders, U., Wilhelm, O., and Olaru, G. (2016). The influence of item sampling on sex differences in knowledge tests. *Intelligence*, 58(October 2019):22–32.
- Skans, O. and Liljeberg, L. (2014). The wage effects of subsidized career breaks. *Empirical Economics*, 47(2):593–617.
- Walker, I. and Zhu, Y. (2008). The college wage premium and the expansion of higher education in the uk. *Scandinavian Journal of Economics*, 110(4):695–709.

A. Data Appendix

In order to make the procedures in this study comparable to related studies and to correct for some possible data issues, we perform some rather standard procedures on the data.

A.1. General remarks

As suggested by [Hanushek et al. \(2015\)](#) and [Hampf et al. \(2020\)](#), we remove the Russian Federation and Indonesia because the samples are not representative, i.e. in Russia the Moscow region is entirely missing, in Indonesia only the Jakarta region was sampled. Furthermore, we exclude all individuals aged 16-19 since we want to focus on those individuals with completed schooling.

A.2. Control variables

The PIAAC survey offers a rich background questionnaire that provides many relevant information on an individuals' personal lives as well as their labour-market characteristics. The most basic controls that are used in all presented regressions are a dummy for being female and age group dummies. The original gender variable provided by the PIAAC dataset is missing for one observation (out of the original 235,622) and is dropped in our entire analysis. Furthermore, a continuous measure for age is available for 181,005/235,622 observations. The missings result from a few countries entirely not providing continuous age information: Austria, Canada, Hungary, New Zealand, Singapore, and the US. These countries only report age in 5-year intervals from 16 to 65. In our study, we drop individuals aged 16-19 (18,865 observations) since we assume that most of these are still in education. Furthermore, in our regressions we only use age group dummies representing ages 20-29, 30-44, 45-54, and 55-65.

The other socio-demographics presented in table 1 refer to an individual living with their spouse or partner and their children. The former is taken as it is from the PIAAC dataset and has 31,080 missings of which only a small part comes from individuals aged 16-19 (564 observations). The remaining missings are within country and range from 3.19% in Singapore to 26.68% in Lithuania. The information on whether an individual has children is taken from the top-coded version of a question on the number of children an individual has (top-coded at 4). The final variable then is 1 if the number of children is greater than 0 and is missing for a total of 3,431 observations (from 0.05 % in Sweden to 13.87% in Cyprus).

An extended set of control variables includes information about individuals' education and occupation details. An indicator for education levels is derived from a variable provided by PIAAC that distinguishes between six categories: Lower secondary or less (ISCED 1, 2, 3C short or less); Upper secondary (ISCED 3A-B, C long); Post-secondary, non tertiary (ISCED 4A-B-C); Tertiary: professional degree (ISCED 5B); Tertiary: bachelor degree (ISCED 5A); Tertiary: master/research degree (ISCED 5A/6); Tertiary: bachelor/master/research degree (ISCED 5A/6). We collapse all tertiary degrees into one indicator as well as the categories for upper and post-secondary education such that we obtain three categories for the education level of an individual (see table 1). This variable is missing for a total of 3,219 observations; this number is composed of within-country missings ranging from 0.00% (Finland) to 13.08%

(Cyprus).

A respondent's area of study in their highest qualification is reported in the categories presented in table 1. In this original version, the variable is missing for 63,842/235,662 observations (of which 12,158 among the 16-19 year olds that are dropped as described above). The remaining 51,684 missing observations are mainly individuals with lower secondary education or less (43,039 observations), so we decided to add this as a category for field of study in order to not lose these observations in the regressions. The remaining 8,645 missing values are composed of within-country missings ranging from 0.12% in Sweden to 51.23% in Israel.

Finally, we often control for an individual's occupation and working status. By doing so, we essentially restrict the sample to employed individuals since only those have non-missing information on their occupation (with the exception of 16 individuals aged 20-65) and their working hours. The categories used for the occupation refer to the 1-digit ISCO standard and are presented in table 1. The variable used has a total of 81,823 missings of which 13,439 come from individuals aged 16-19. The remaining 68,384 missing values almost entirely come from individuals who report not to be employed at the moment (unemployed or out of the labour force), only 2,684 employed individuals are missing this variable. Again, this comes from within-country missings ranging from 0.37% in Finland to 11.93% in Norway. Instead, the variables on employment status refer to an individual reporting to be employed as opposed to unemployed or out of the labour force as well as the reported working hours. The employment status of an individual is missing for 3,247 observations, most of which are aged above 19 and hence stay in our analysis (between 0.02% and 13.12% per country). Exploiting a question asking respondents to report their weekly working hours, we then code a worker as employed full-time if the reported hours exceed 29 hours/week. The resulting variable is missing for 79,668 individuals of which 13,158 are 16-19 years old and will hence be excluded from our analysis. All non-missing values come from employed individuals and only 865 of the latter have missing information on their full-time status. These are again within-country missings ranging from 0.08% in Ireland to 2.4% in Israel.

A.3. *Sampling weights*

In order to give the same weight to each country in pooled regressions, we also standardize the sampling weights. The variable *spfwt0* contains the final full sample weight provided by the OECD that makes sure each country is representative in a given dataset, both in size as well as regarding relevant demographic characteristics. Since we do not wish to represent different sizes of countries in our pooled regressions we adjust this variable to sum up to 1 in a country instead of its effective size. These adjusted weights are then used in our regressions throughout (if not specified otherwise).

A.4. *Skill measures*

Since in this study we are mainly interested in individual determinants and consequences of skill levels and gaps rather than international comparisons, we standardize the skill measures throughout the paper (if not specified otherwise). The three skill domains available in the PIAAC dataset (numeracy, literacy, problem-solving) are originally reported on a 500-point

scale (OECD, 2016a). We standardize these measures to have mean 0 and standard deviation within each country (using sampling weights). Throughout the analysis, we then use the first plausible value of each skill measure (following Hanushek et al. (2015)).

A.5. Wages

Following Hanushek et al. (2015) and Hampf et al. (2020), among others, we perform a few important modifications of the available wage measures.

A first important thing to notice is that not all countries provide continuous information on their respondents' wages. Peru does not provide any wage information at all whereas a number of countries only report the wage decile an individual is positioned in (Austria, Canada, Germany, Hungary, Singapore, Sweden, Turkey, and the US). For Germany, we are able to obtain a Scientific Use File that contains continuous wage measures. For Austria, Canada, Sweden, and the US, (as in Hanushek et al. (2015)) we are able to obtain country-specific information on each decile's median wage such that we can assign the decile median to each individual reported to be in the respective country-specific wage decile. This leaves us with four countries without wage information: Hungary, Peru, Singapore, and Turkey.

In the PIAAC questionnaire, individuals were first asked about their preferred way of reporting their salary (*What is the easiest way for you to tell us your usual gross wage or salary for your current job?*). The response options range from the temporal frames *per hour* to *per year*, but there is also an option for piece rate. Depending on the answer to this question, individuals are forwarded to the question asking them to report the gross salary in their preferred way. Furthermore, if individuals are unsure or unwilling to report their salaries precisely, they are forwarded to a question where they get presented wage categories on the basis of their respective national earnings distribution in which they can place themselves as an estimate of their own salary. Similarly, bonuses and other additional payments are assessed. For self-employed individuals, only monthly earnings are asked.¹²

In this paper, we mainly focus on hourly wages due to their better comparability across individuals in different types of employment. The corresponding variables for hourly wages are reported both with and without bonuses for wage and salary earners, as well as ppp-adjusted and non ppp-adjusted (in US dollars). Wage deciles are available both for hourly earnings with and without bonuses. In order to obtain these measures of hourly wages from the reported earnings as described above, PIAAC performs a conversion of the given answers into both hourly and monthly earnings as described in OECD (2016b), chapter 20. The description here will focus on hourly earnings, details for monthly earnings can be found in OECD (2016b), chapter 20. As for hourly earnings, all salaries reported in categories other than *per hour* are converted into hourly salaries using the information about weekly hours worked from a previous question. For respondents who reported their earnings in intervals as described above, an imputation mechanism was developed. The imputation method would match each respondent with a "similar" respondent who reported earnings directly, where "similar" would be defined on the basis of highest education, skill level, age, gender and so on. The precise earnings of

¹²See OECD (2016b) and http://www.oecd.org/skills/piaac/BQ_MASTER.HTM, last accessed March 17, 2021.

this "similar" respondent were then used to impute the respective earnings of the respondent which reported only wage intervals. This was done equivalently for bonuses/additional payments and monthly earnings. Furthermore, a variable indicating imputation of precise earnings was included (OECD, 2016b).

The readily available wage measures from the PIAAC dataset could in principle be used directly to conduct empirical analyses. Nonetheless, we perform some further adjustments to the wage data, following the procedure in Hanushek et al. (2015) and Hampf et al. (2020). As a first step, we assign decile medians as hourly earnings to further 21 observations, including a dummy indicating this procedure. In a second step, we trim 1 percent at the bottom and the top of the wage distribution in each country in order to reduce the possible influence of outliers. Finally, all wage measures are logged.

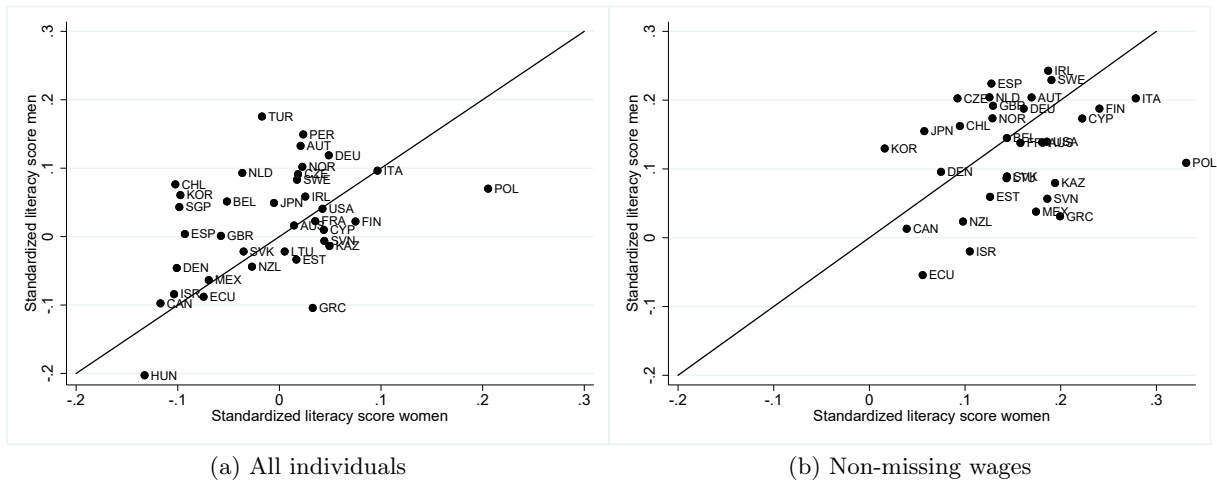
A.6. German panel dataset

As mentioned above, Germany resurveyed individuals from the 2012 PIAAC sample in order to create a small panel dataset. Mainly, we apply the same corrections/transformations to the dataset as described in subsections A.4 and A.5, this subsection will focus on the differences only.

The resampling of German respondents took place in 2014, 2015, and 2016. In 2014, only household members aged 18 or above of the 2012 respondents were surveyed. In 2015, both original 2012 respondents and their partners living in the household were surveyed almost identically to the original questionnaire in 2012. The last sampling in 2016 again surveyed household members aged 18 or above from the respective households. Since numeracy skills were only measured again in a comparable way in 2015, we focus on the samples from 2012 and 2015 in the analysis of the German subsample. Wages in 2015 are not available in a continuous measure but only in wage intervals. Hence, individuals are assigned the midpoint of this interval as their wage measure. Hanushek et al. (2015) show that this procedure in general provides very similar results to the use of continuous wages. In 2012, we have continuous measures for wages provided by PIAAC such that we decided to use the best available measure in each year.

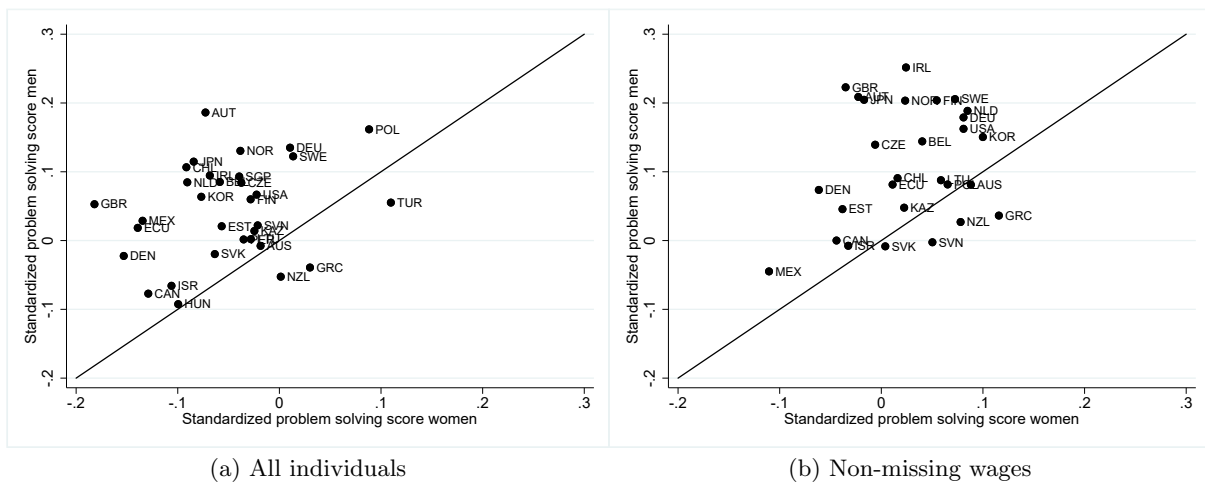
B. Appendix: Supplementary Figures and Tables

Figure B.1: Gender-specific literacy scores by country



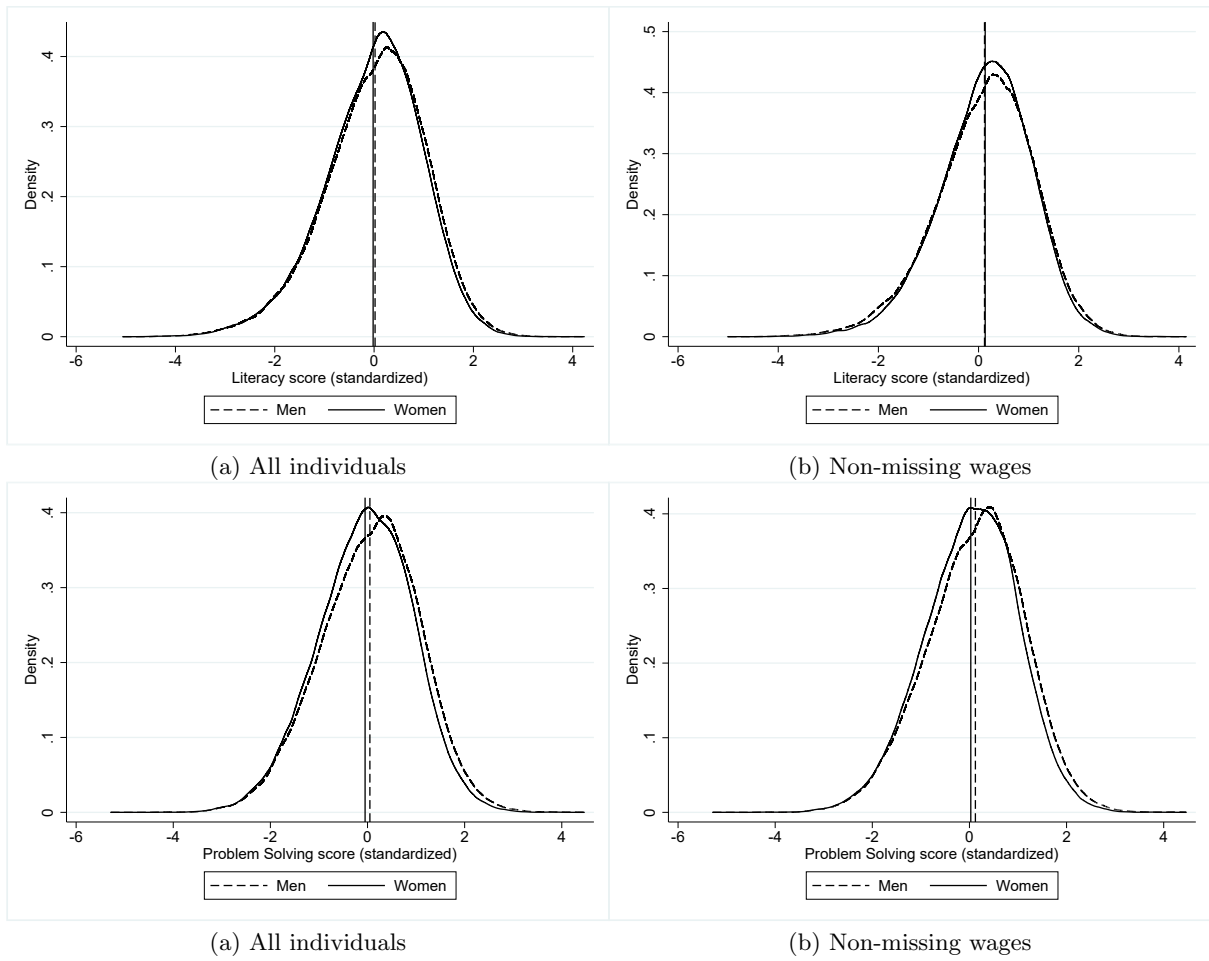
Notes: Standardized literacy scores for men and women aged 20-65 by country. Standardization uses individuals' sampling probability. The graph additionally includes the 45-degree line to depict potential equality of test scores. Sample contains all individuals with non-missing literacy scores. Data source: PIAAC international PUF 2012.

Figure B.2: Gender-specific problem solving scores by country



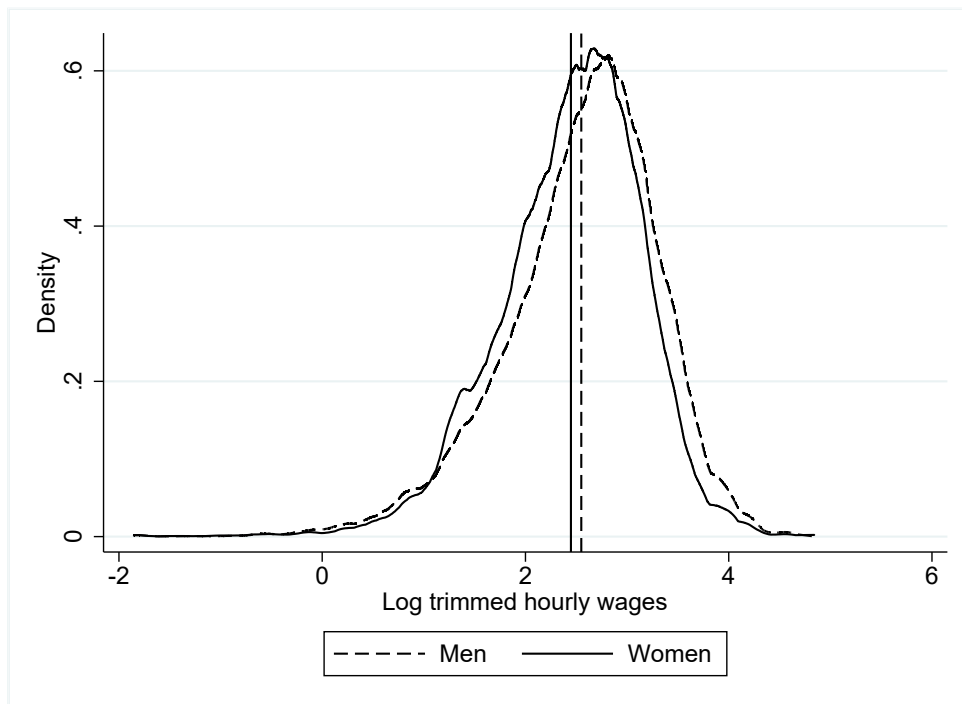
Notes: Standardized scores for problem solving in technology-rich environments for men and women aged 20-65 by country. Standardization uses individuals' sampling probability. The graph additionally includes the 45-degree line to depict potential equality of test scores. Sample contains all individuals with non-missing problem-solving scores. Results look similar when just considering countries with earnings information (results available upon request). Data source: PIAAC international PUF 2012.

Figure B.3: Test scores in literacy and problem solving, by gender



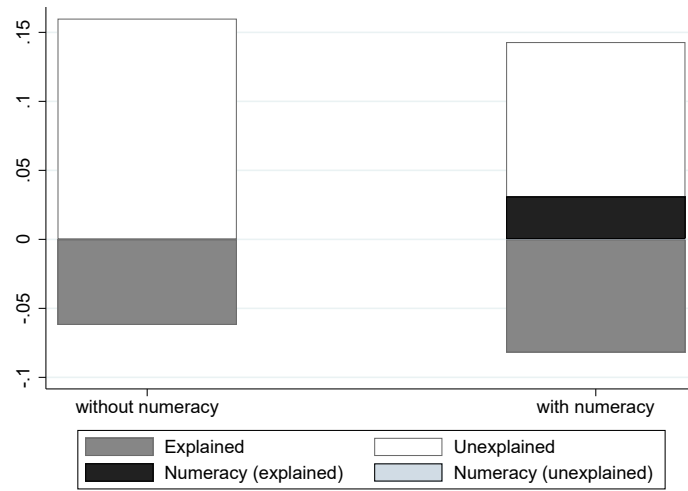
Notes: Standardized literacy and problem solving scores for men and women. Standardization uses individuals' sampling probability. Vertical lines represent the respective means for women and men. Sample contains all individuals with non-missing skill measures. Results look similar when just considering countries with earnings information (results available upon request). Data source: PIAAC international PUF 2012.

Figure B.4: Distribution of gross hourly wages, by gender

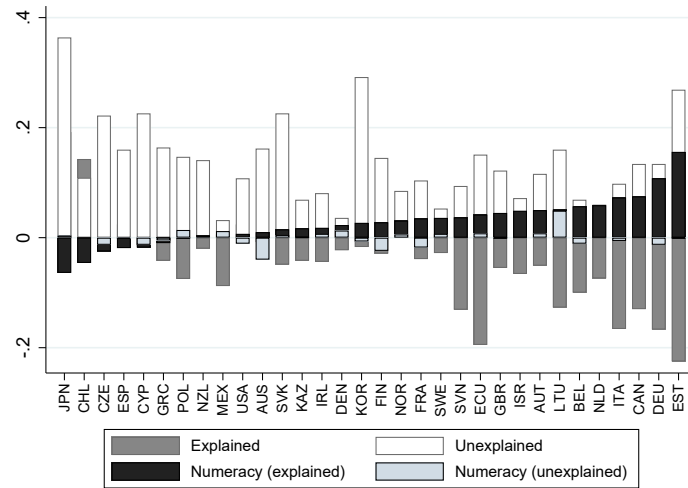


Notes: Log trimmed gross hourly wages (ppp-adjusted) for men and women. Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Vertical lines represent the respective means for women and men. Sample contains all individuals with wage information. Data source: PIAAC international PUF 2012.

Figure B.5: Role of skills in gender gap formation



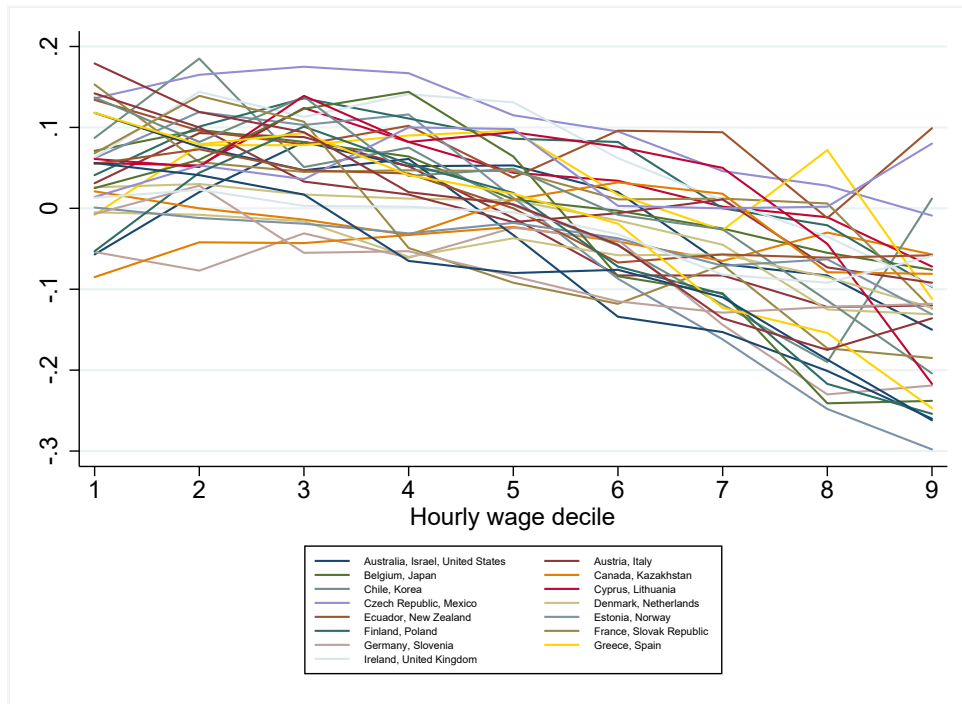
(A) On average



(B) By country

Notes: Panel (A): Oaxaca-Blinder decomposition of gender gaps in hourly wages for employed individuals aged 20-65. Explanatory variables used: age groups, children, education, field of study, occupation, and country dummies. Numeracy scores are added as explanatory variables in second bar. Panel (B): Oaxaca-Blinder decomposition of gender gaps in hourly wages for employed individuals aged 20-65 by country. Explanatory variables used: numeracy scores, age groups, children, education, field of study, occupation, and country dummies. Data source: PIAAC international PUF 2012.

Figure B.6: Returns to numeracy for women relative to men, by country



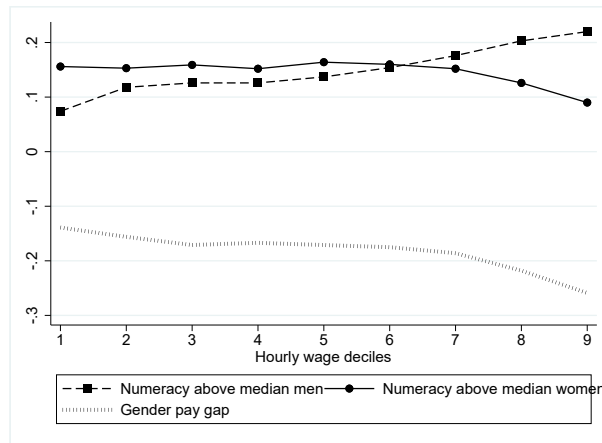
Notes: Plot of the coefficients presented in equation 1 corresponding to unconditional quantile regressions with full controls (age groups, education levels, field of study, occupation, full-time status, children, and children*female) at each wage decile border. Graphs represent returns to numeracy levels for women relative to men ($\hat{\delta}$) as described above. Sample contains all individuals with non-missing wages and numeracy scores as well as the respective controls. Data source: PIAAC international PUF 2012.

Table B.1: Composition of PIAAC data by country

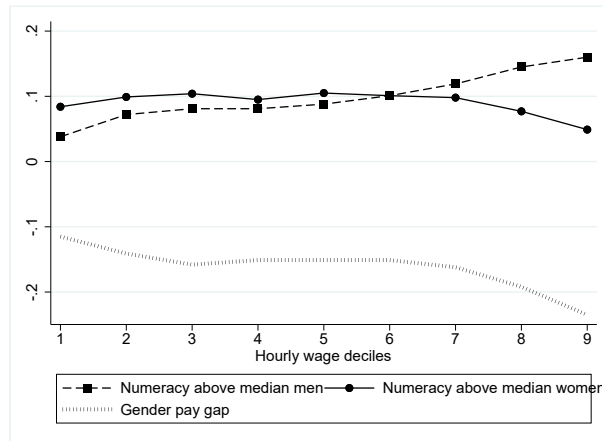
Country	Isocode	2011/12	2014/15	2017	Numeracy	Literacy	Problem solving	Wages
Australia	AUS	x			6,974	6,974	5,217	4,266
Austria	AUT	x			4,597	4,597	3,451	2,824 (D)
Belgium	BEL	x			4,542	4,542	3,755	2,751
Canada	CAN	x			24,462	24,462	19,183	15,248 (D)
Chile	CHL		x		4,770	4,770	2,954	2,298
Cyprus	CYP	x			4,093	4,093	0	2,149
Czech Republic	CZE	x			5,357	5,357	3,984	2,581
Denmark	DEN	x			6,770	6,770	5,620	4,447
Ecuador	ECU			x	4,964	4,964	1,991	1,652
Estonia	EST	x			7,043	7,043	4,715	3,999
Finland	FIN	x			5,042	5,042	4,100	3,252
France	FRA	x			6,374	6,374	0	3,719
Germany	DEU	x			4,871	4,871	4,049	3,279
Greece	GRC		x		4,684	4,684	2,965	1,260
Hungary	HUN			x	5,719	5,719	3,700	0
Ireland	IRL	x			5,626	5,626	3,788	2,788
Israel	ISR		x		4,722	4,722	3,123	2,605
Italy	ITA	x			4,367	4,367	0	1,978
Japan	JPN	x			4,806	4,806	3,034	3,239
Kazakhstan	KAZ			x	5,706	5,706	4,205	2,680
Korea	KOR	x			6,081	6,081	3,998	3,095
Lithuania	LTU		x		4,783	4,783	3,421	2,746
Mexico	MEX			x	5,616	5,616	2,008	2,253
Netherlands	NLD	x			4,655	4,655	4,139	2,997
New Zealand	NZL		x		5,457	5,457	4,922	3,314
Norway	NOR	x			4,455	4,455	3,872	3,408
Peru	PER			x	6,538	6,538	2,867	0
Poland	POL	x			8,302	8,302	5,129	3,839
Singapore	SGP		x		4,887	4,887	3,598	0
Slovak Republic	SVK	x			5,213	5,213	3,110	2,510
Slovenia	SVN		x		4,922	4,922	3,633	2,233
Spain	ESP	x			5,504	5,504	0	2,471
Sweden	SWE	x			4,080	4,080	3,591	2,872 (D)
Turkey	TUR		x		4,854	4,854	2,038	0
United Kingdom	GBR	x			8,311	8,311	6,850	4,728
United States	USA	x		x	4,553	4,553	3,786	2,734 (D)
Total	36	23	8	6	213,700	213,700	136,796	106,215

Notes: The table contains the list of participating countries and their ISO codes, and an indication of the year when the survey was conducted (the first round in 2011/12, the second round in 2014/15, or the third round in 2017). Additionally, the table lists the number of non-missing observations available for each of the skill domains (numeracy, literacy, problem solving) and wages. (D) denotes countries that provide wage information only by belonging to a decile. Also note that the list does not include Russia and Indonesia, following the recommendation in the official PIAAC reports. For details also see Appendix A and <https://www.oecd.org/skills/piaac/about/#d.en.48111>. Data source: PIAAC international PUF 2012, own calculations.

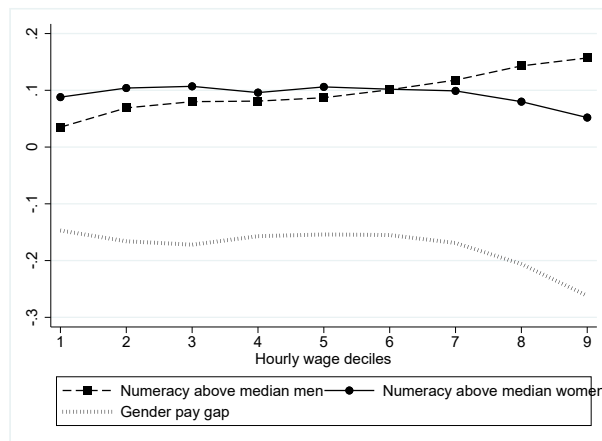
Figure B.7: Returns to numeracy levels with additional controls



(A) Additional controls: education level and field of study



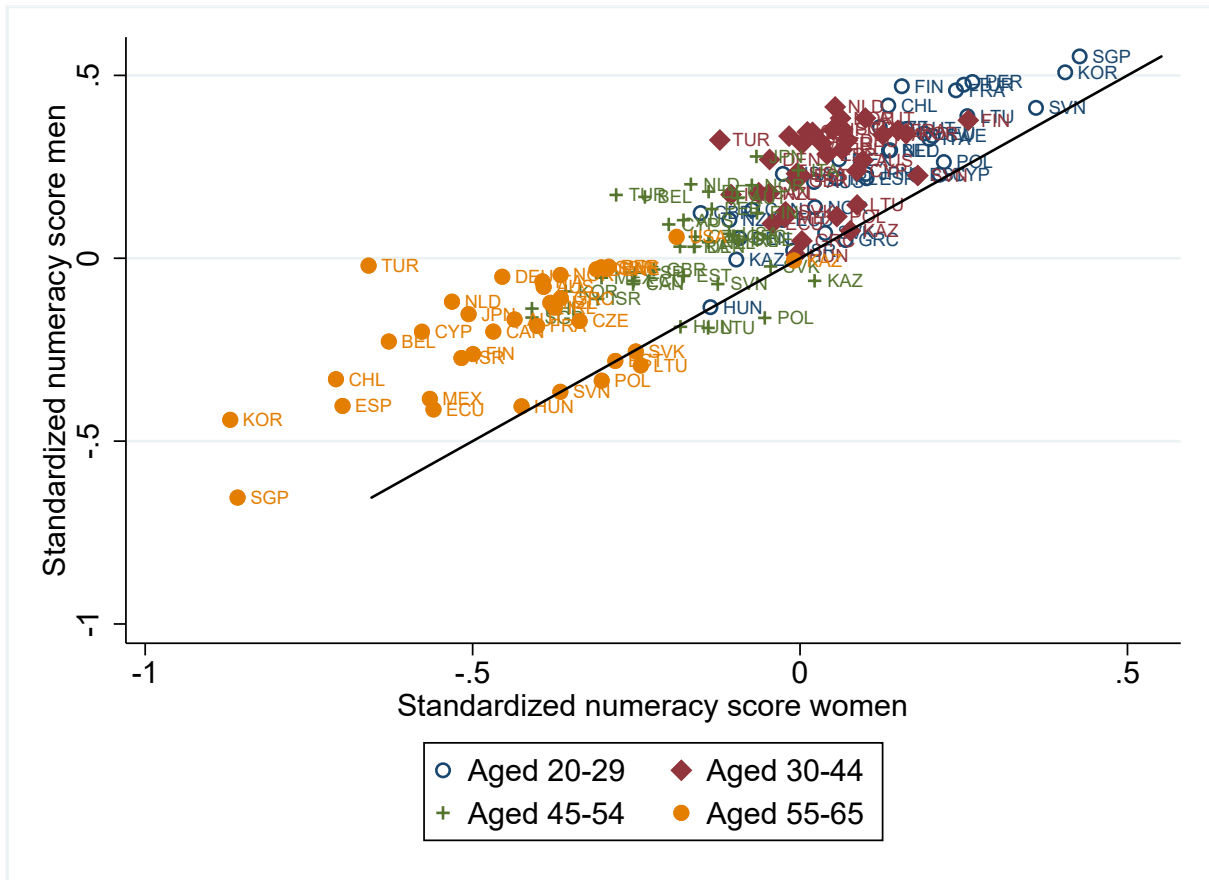
(B) Additional controls: occupation category



(C) Additional control: full-time indicator

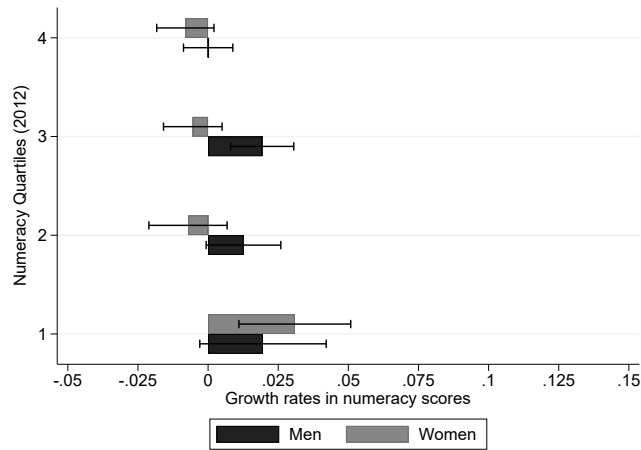
Notes: Plot of the coefficients presented in equation 1 corresponding to unconditional quantile regressions with further controls level of education, field of study, occupation, and a full-time indicator (in addition to age groups and country fixed effects) at each wage decile border. Level of education, field of study, and occupation are measured as presented in table 1. Field of study has an additional category for individuals with the lowest level of education and missing information on field of study. The full-time indicator takes on the value 1 if an individual is in full-time employment (more than 29 working hours per week) and 0 otherwise. For description of graphs see notes of figure 4. The corresponding tables can be found in figure B.3, figure B.4, and figure B.5. Numeracy scores are standardized using individuals' sampling probability. Sample contains all individuals aged 20-65 with and non-missing wages and numeracy scores. Data source: PIAAC international PUF 2012.

Figure B.8: Gender-specific numeracy scores by country and age groups

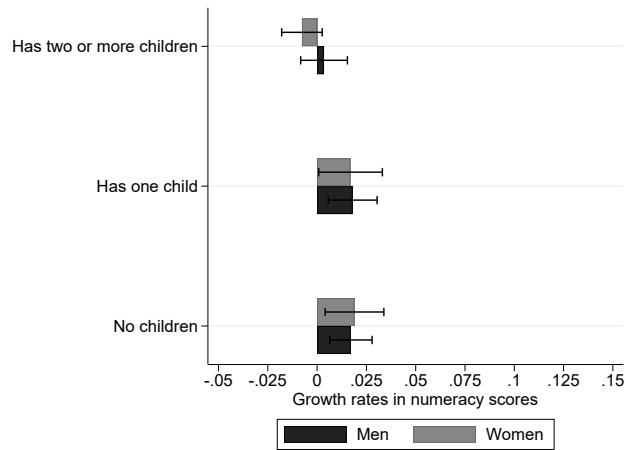


Notes: Standardized numeracy scores for men and women aged 20-65 by country and age groups. Standardization uses individuals' sampling probability. The graph additionally includes the 45-degree line to depict potential equality of test scores. Sample contains all individuals with non-missing numeracy scores. Results look similar when just considering countries with earnings information or only individuals with non-missing wages (results available upon request). Data source: PIAAC international PUF 2012.

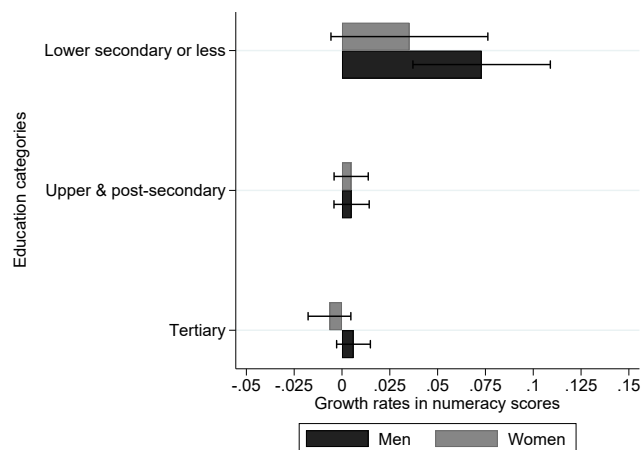
Figure B.9: Change in numeracy test score between 2012 and 2015 (I)



(A) By quartile of numeracy score 2012



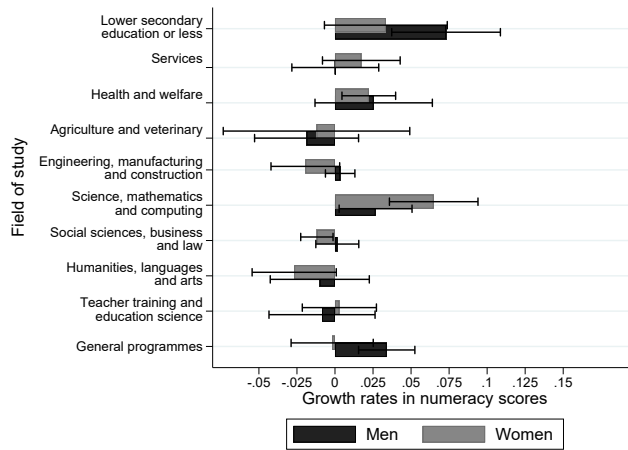
(B) by number of children 2012



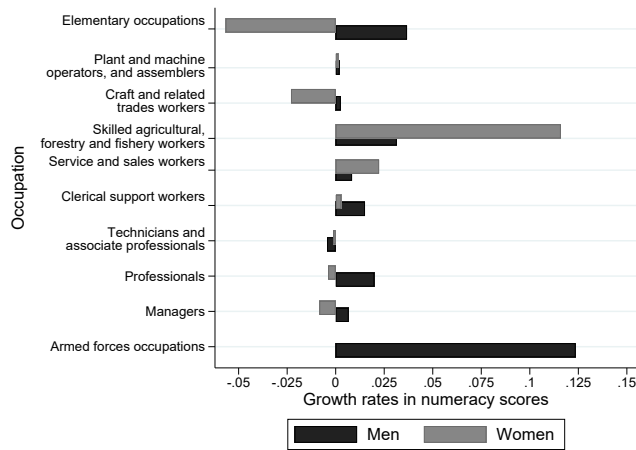
(C) by education level 2012

Notes: Growth rates in numeracy scores for men and women in Germany between 2015 and 2012 by numeracy quartiles (A), number of children (B), and education level (C), all in 2012. Growth rates are calculated by dividing the difference between 2015 and 2012 numeracy scores by 2012 numeracy scores. Age groups refer to the age reported in 2012. Confidence intervals are added for each bar. Sample contains all individuals with non-missing numeracy scores in 2012 and 2015, as well as the respective categories. Data source: PIAAC-L German SUF 2015 and 2012.

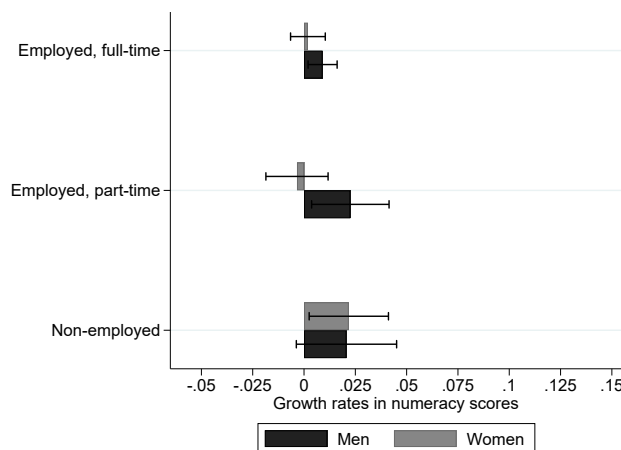
Figure B.10: Change in numeracy test score between 2012 and 2015 (II)



(A) by field of study 2012



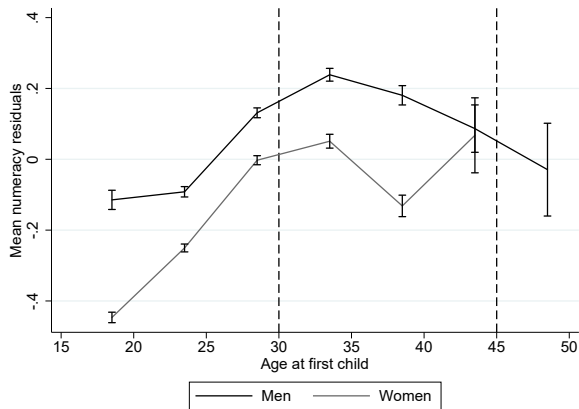
(B) occupational category 2012



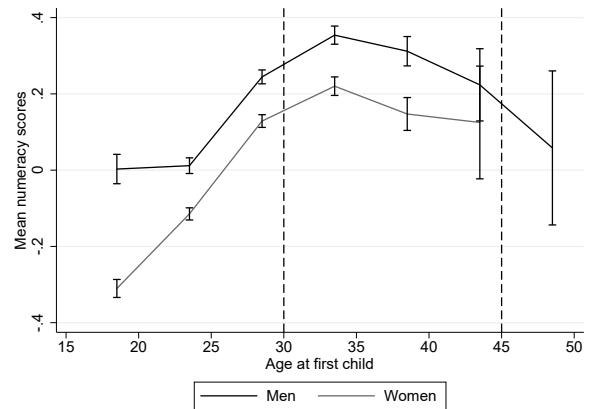
(C) by employment status 2012

Notes: Growth rates in numeracy scores for men and women in Germany between 2015 and 2012 by field of study (A), number of occupation (B), and employment status (C), all in 2012. Growth rates are calculated by dividing the difference between 2015 and 2012 numeracy scores by 2012 numeracy scores. Age groups refer to the age reported in 2012. Confidence intervals are added for each bar. Sample contains all individuals with non-missing numeracy scores in 2012 and 2015, as well as the respective categories. Data source: PIAAC-L German SUF 2015 and 2012.

Figure B.11: Numeracy levels by gender and age at the first childbirth

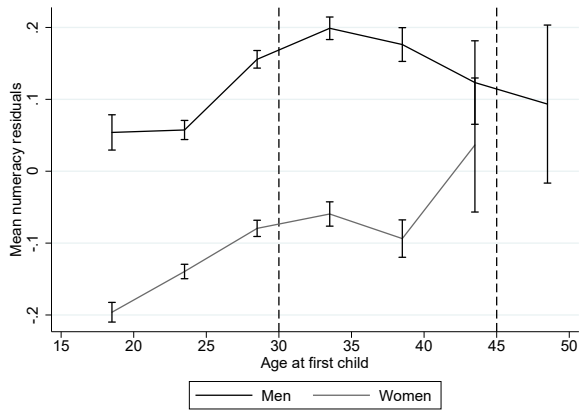


(a) All individuals

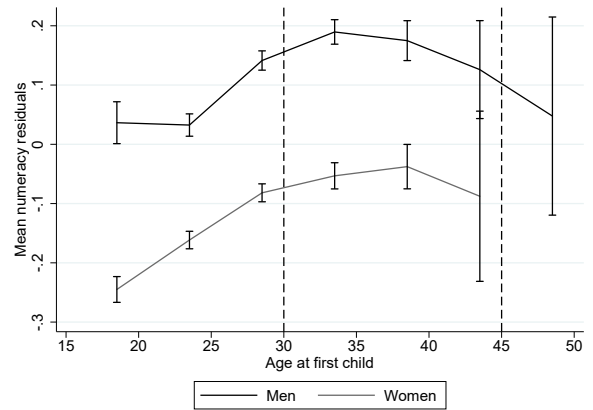


(b) Non-missing wages

(A) Unconditional



(a) All individuals

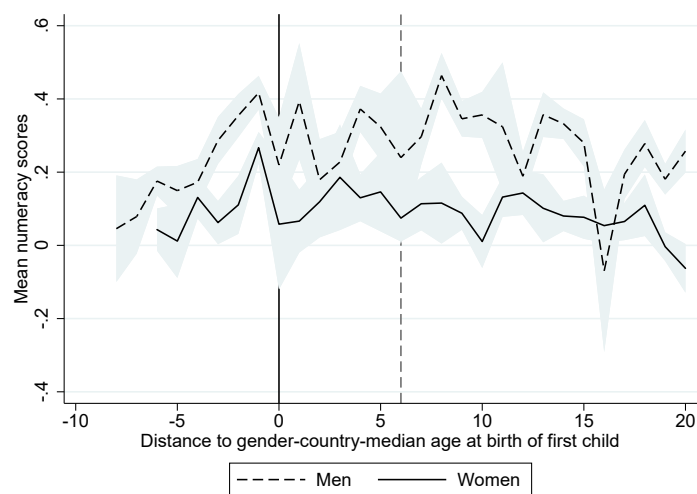


(b) Non-missing wages

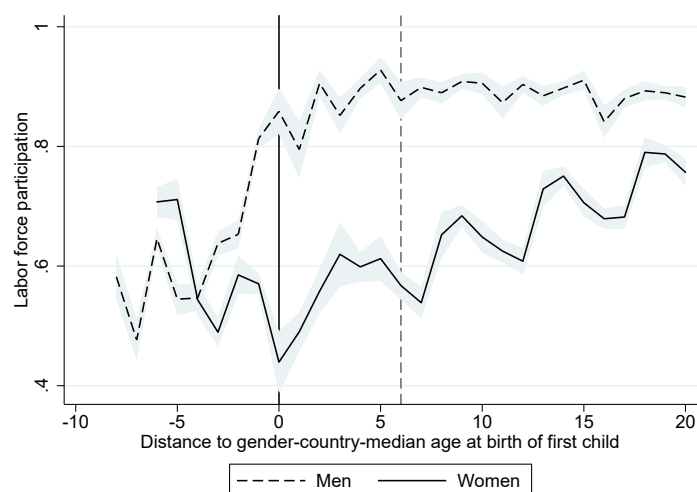
(B) Residual, after conditioning on educational levels

Notes: Mean standardized numeracy scores by age at birth of first child (in 5-year intervals) for men and women aged 20-65. Panel (A) presents raw numeracy scores, panel (B) plots the residuals of a least squares regression of numeracy scores on age groups, education levels, and country dummies, using sampling weights. Confidence intervals for each data point are added, vertical lines represent cutoffs of age groups used in the regressions at ages 30, 45, and 55. Standardization uses individuals' sampling probability. Sample contains all individuals with non-missing numeracy scores, age, and child information. Data source: PIAAC international PUF 2012.

Figure B.12: Numeracy levels among employed and participation rates around the age of first birth



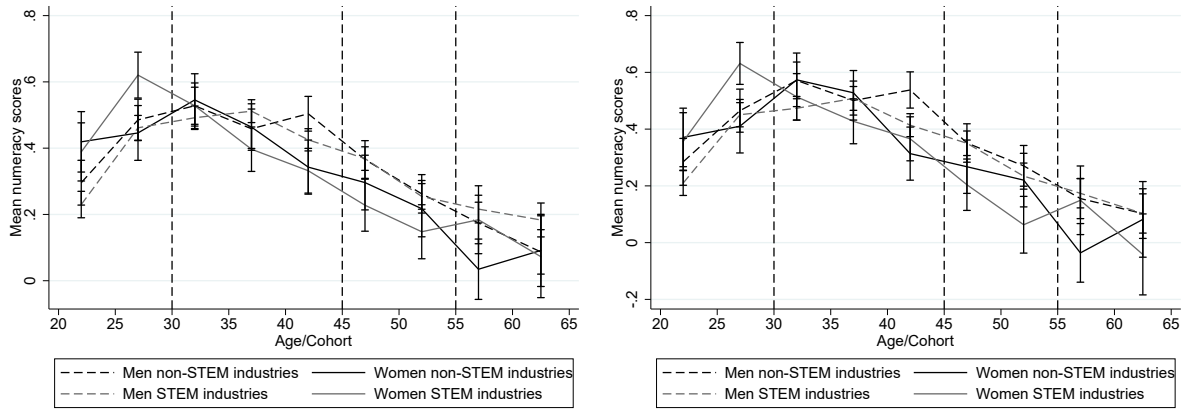
(A) numeracy levels among employed



(B) labour force participation

Notes: Panel (A): Mean standardized numeracy scores by distance to the country-gender-specific age at birth of the first child for men and women with children (positive distance) and without children (negative distance) for individuals with non-missing wages. Confidence bands are added, vertical lines represent cutoffs for individuals with and without children (solid line at 0) and children's ages for individuals with children (dashed line at 6). Individuals with children aged 0-5 form the group with distances 0-5, equivalently for children aged 6 or above. Sample contains all individuals aged 20-65 with non-missing numeracy scores, non-missing wages, age, and child information. Panel (B): labour force participation (employed or self-employed) by distance to the country-gender-specific age at birth of the first child for men and women with children (positive distance) and without children (negative distance). Confidence bands are added, vertical lines represent cutoffs for individuals with and without children (solid line at 0) and children's ages for individuals with children (dashed line at 6). Individuals with children aged 0-5 form the group with distances 0-5, equivalently for children aged 6 or above. Sample contains all individuals aged 20-65 with non-missing employment status, age, and child information. Data source: PIAAC international PUF 2012.

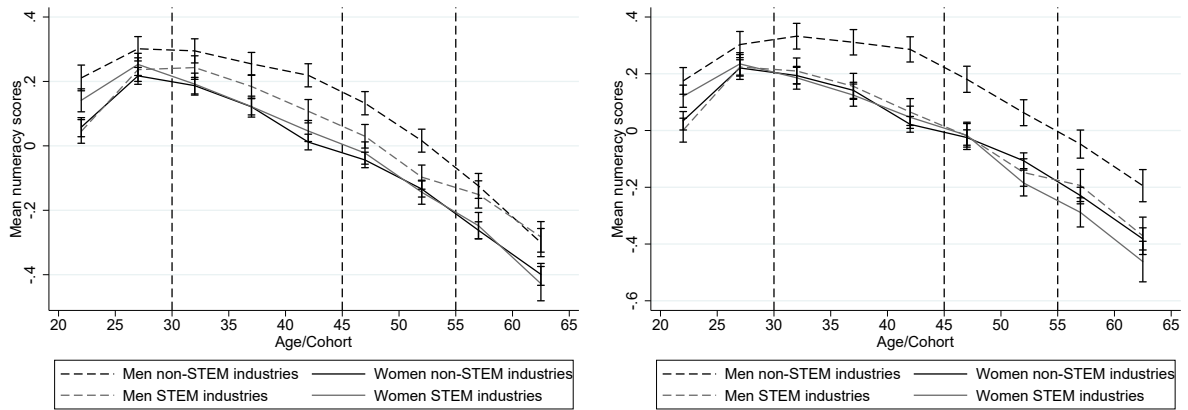
Figure B.13: Numeracy levels over cohorts STEM v non-STEM industry



(a) All individuals

(b) Non-missing wages

(A) for respondents graduated in STEM field of study



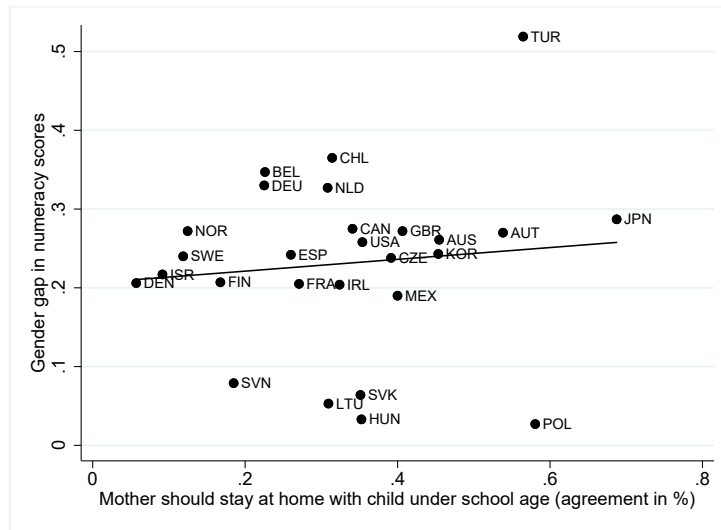
(a) All individuals

(b) Non-missing wages

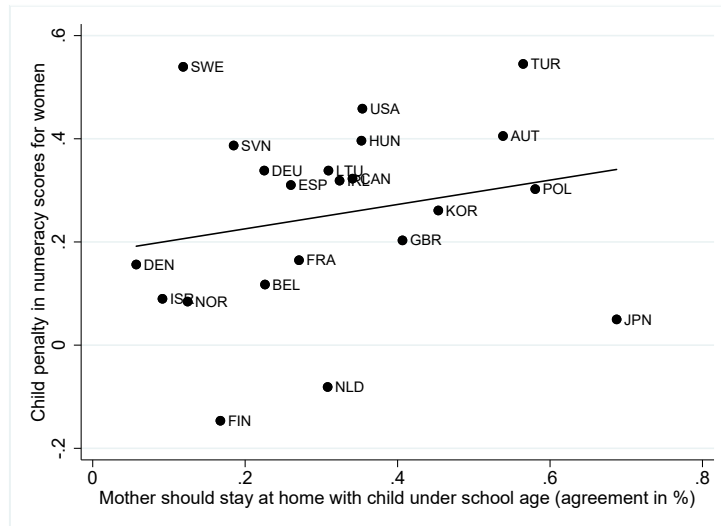
(B) for respondents graduated in non-STEM field of study

Notes: Mean standardized numeracy scores by age (in 5-year intervals) for men and women with STEM (A)/non-STEM (B) fields of study in STEM v non-STEM industries. Confidence intervals for each data point are added, vertical lines represent cutoffs of age groups in the regressions at age 30, 45, and 55. Standardization uses individuals' sampling probability. Sample contains all employed individuals with non-missing numeracy scores, age, and field of study. Data source: PIAAC international PUF 2012.

Figure B.14: Relationship between numeracy gaps and norms, by country



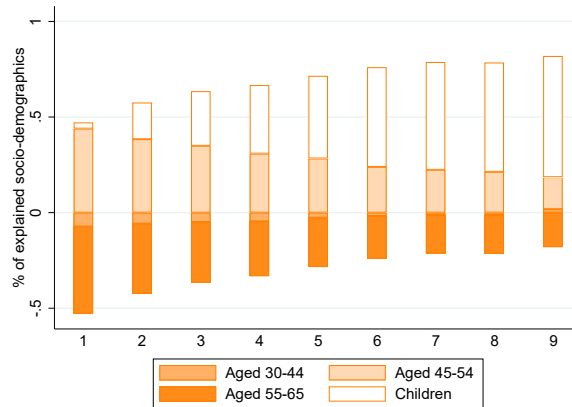
(A) gender numeracy gap



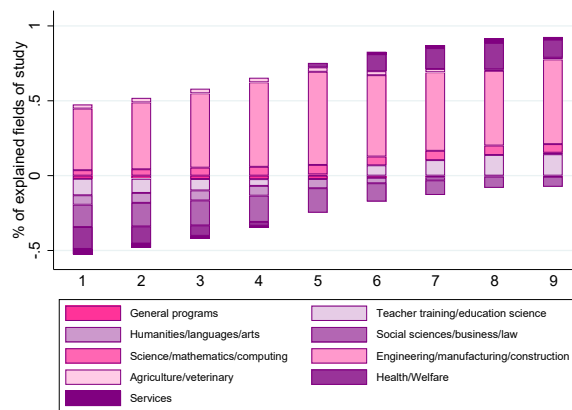
(B) child penalty

Notes: Panel (A): Gender pay gap in standardized numeracy scores for men and women aged 20-65 by country plotted against the percentage in agreement to the statement "Do you think that women should work outside the home full-time, part-time or not at all under the following circumstances?" Option: "Stay at home when there is a child under school age." by country, including a linear fit. Panel (B): Child penalties as obtained in figure 8 by country plotted against the percentage in agreement to the statement "Do you think that women should work outside the home full-time, part-time or not at all under the following circumstances?" Option: "Stay at home when there is a child under school age." by country, including a linear fit. Child penalties for women are calculated as the difference between the long-term after-child numeracy scores (the average of numeracy scores 5 to 10 years after the median gender-country age at first child birth, as in Kleven et al. (2019)) and the average of numeracy scores in the five years before the median gender-country age at first child birth. Sample contains individuals aged 20-65 with non-missing numeracy scores from PIAAC and countries with non-missing norms information from ISSP 2012. Data source: PIAAC international PUF 2012 and data on norms from the 2012 ISSP questionnaire on "Family and Changing Gender Roles".

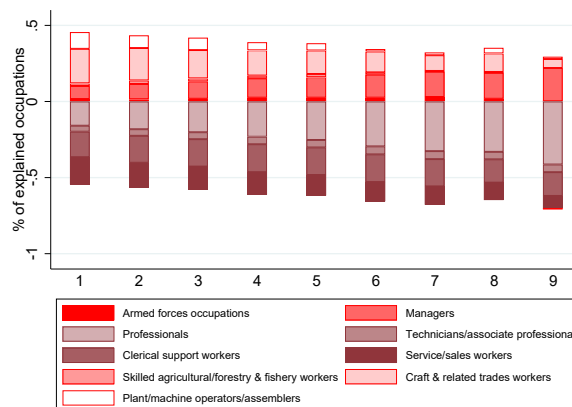
Figure B.15: Oaxaca-style decomposition the gender numeracy gap: explained part, selected groups



(A) Explained: Socio-demographics



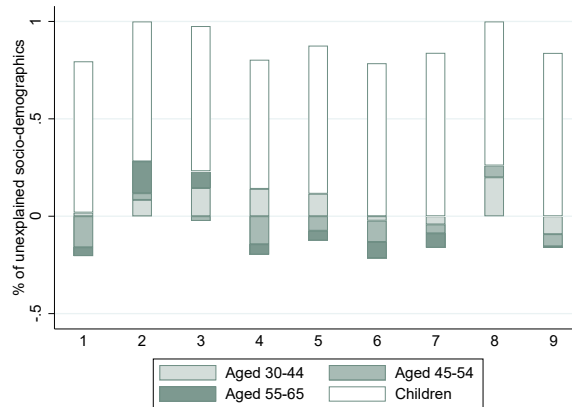
(B) Explained: Field of study



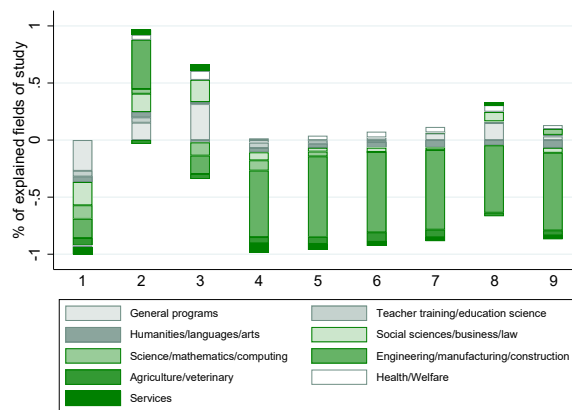
(C) Explained: Occupation

Notes: Explained part of a detailed Oaxaca-Blinder type decomposition of gender numeracy gaps by numeracy decile using the command *oaxaca_rif*. Explanatory variables presented here: age groups and children (A), field of study (B), and occupation (C). Results look similar when just considering countries with earnings information or only individuals with non-missing wages (results available upon request). Data source: PIAAC international PUF 2012.

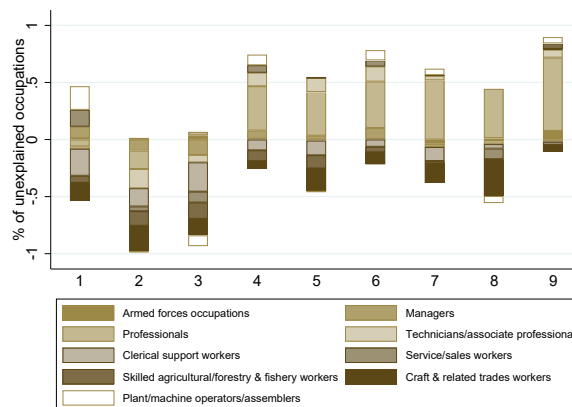
Figure B.16: Oaxaca-style decomposition the gender numeracy gap: unexplained part, selected groups



(A) Unexplained: Socio-demographics



(B) Unexplained: Field of study



(C) Unexplained: Occupation

Notes: Unexplained part of a detailed Oaxaca-Blinder type decomposition of gender numeracy gaps by numeracy decile using the command *oaxaca_rif*. Explanatory variables presented here: age groups and children (A), field of study (B), and occupation (C). Results differ slightly when just considering countries with earnings information or only individuals with non-missing wages (results available upon request). Data source: PIAAC international PUF 2012.

Table B.2: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.168*** (0.015)	-0.147*** (0.011)	-0.168*** (0.009)	-0.152*** (0.008)	-0.154*** (0.007)	-0.136*** (0.007)	-0.121*** (0.007)	-0.098*** (0.007)	-0.093*** (0.008)
Aged 30-44	0.147*** (0.014)	0.177*** (0.010)	0.231*** (0.009)	0.266*** (0.007)	0.300*** (0.007)	0.300*** (0.006)	0.296*** (0.006)	0.279*** (0.006)	0.248*** (0.008)
Aged 45-54	0.098*** (0.015)	0.146*** (0.011)	0.219*** (0.009)	0.283*** (0.008)	0.341*** (0.007)	0.367*** (0.007)	0.381*** (0.007)	0.375*** (0.007)	0.366*** (0.009)
Aged 55-65	0.067*** (0.017)	0.138*** (0.012)	0.209*** (0.010)	0.271*** (0.009)	0.337*** (0.009)	0.368*** (0.008)	0.387*** (0.008)	0.390*** (0.009)	0.400*** (0.012)
Numeracy above median	0.191*** (0.014)	0.224*** (0.010)	0.232*** (0.009)	0.232*** (0.007)	0.254*** (0.007)	0.274*** (0.007)	0.297*** (0.007)	0.334*** (0.008)	0.365*** (0.010)
Numeracy above median * Female	0.073*** (0.020)	0.035* (0.014)	0.036** (0.012)	0.024* (0.010)	0.020* (0.010)	-0.002 (0.009)	-0.028** (0.009)	-0.082*** (0.010)	-0.139*** (0.013)
Education levels	No	No	No	No	No	No	No	No	No
Field of study	No	No	No	No	No	No	No	No	No
Occupation	No	No	No	No	No	No	No	No	No
Full-time indicator	No	No	No	No	No	No	No	No	No
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106206	106206	106206	106206	106206	106206	106206	106206	106206

Notes: Corresponding table for figure 4. Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B-3: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.221*** (0.017)	-0.191*** (0.012)	-0.204*** (0.010)	-0.193*** (0.008)	-0.198*** (0.008)	-0.180*** (0.007)	-0.162*** (0.007)	-0.141*** (0.007)	-0.129*** (0.009)
Aged 30-44	0.119*** (0.014)	0.144*** (0.010)	0.196*** (0.009)	0.240*** (0.007)	0.270*** (0.007)	0.271*** (0.006)	0.269*** (0.006)	0.251*** (0.006)	0.214*** (0.008)
Aged 45-54	0.095*** (0.015)	0.137*** (0.011)	0.207*** (0.009)	0.279*** (0.008)	0.336*** (0.007)	0.365*** (0.007)	0.383*** (0.007)	0.376*** (0.007)	0.363*** (0.009)
Aged 55-65	0.067*** (0.017)	0.130*** (0.012)	0.198*** (0.010)	0.270*** (0.009)	0.333*** (0.008)	0.367*** (0.008)	0.392*** (0.008)	0.394*** (0.009)	0.404*** (0.012)
Numeracy above median	0.074*** (0.014)	0.118*** (0.011)	0.126*** (0.009)	0.126*** (0.008)	0.137*** (0.007)	0.154*** (0.007)	0.176*** (0.007)	0.203*** (0.008)	0.220*** (0.010)
Numeracy above median * Female	0.082*** (0.020)	0.035* (0.014)	0.032** (0.012)	0.026* (0.010)	0.028** (0.010)	0.005 (0.009)	-0.024* (0.009)	-0.077*** (0.010)	-0.130*** (0.013)
Education levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	No	No	No
Full-time indicator	No	No	No	No	No	No	No	No	No
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103443	103443	103443	103443	103443	103443	103443	103443	103443

Notes: Corresponding table for figure B.7 (A). Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.4: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.161*** (0.017)	-0.168*** (0.012)	-0.181*** (0.010)	-0.165*** (0.008)	-0.168*** (0.008)	-0.151*** (0.007)	-0.141*** (0.007)	-0.125*** (0.008)	-0.124*** (0.010)
Aged 30-44	0.087*** (0.014)	0.116*** (0.010)	0.167*** (0.009)	0.209*** (0.007)	0.237*** (0.007)	0.237*** (0.006)	0.235*** (0.006)	0.216*** (0.006)	0.179*** (0.008)
Aged 45-54	0.058*** (0.015)	0.104*** (0.011)	0.172*** (0.009)	0.242*** (0.008)	0.296*** (0.007)	0.323*** (0.007)	0.340*** (0.007)	0.331*** (0.007)	0.318*** (0.009)
Aged 55-65	0.030 (0.017)	0.095*** (0.012)	0.159*** (0.010)	0.229*** (0.009)	0.289*** (0.008)	0.320*** (0.008)	0.345*** (0.008)	0.343*** (0.009)	0.349*** (0.011)
Numeracy above median	0.038* (0.015)	0.072*** (0.011)	0.081*** (0.009)	0.081*** (0.008)	0.088*** (0.007)	0.101*** (0.007)	0.119*** (0.007)	0.145*** (0.008)	0.160*** (0.010)
Numeracy above median * Female	0.046* (0.020)	0.027 (0.015)	0.023 (0.012)	0.014 (0.010)	0.017 (0.010)	-0.000 (0.009)	-0.021* (0.009)	-0.067*** (0.010)	-0.111*** (0.013)
Education levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full-time indicator	No	No	No	No	No	No	No	No	No
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102602	102602	102602	102602	102602	102602	102602	102602	102602

Notes: Corresponding table for figure B.7 (B). Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.5: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.200*** (0.018)	-0.200*** (0.012)	-0.200*** (0.010)	-0.173*** (0.008)	-0.173*** (0.008)	-0.155*** (0.007)	-0.149*** (0.007)	-0.143*** (0.008)	-0.158*** (0.010)
Aged 30-44	0.102*** (0.014)	0.128*** (0.010)	0.174*** (0.009)	0.213*** (0.007)	0.239*** (0.007)	0.239*** (0.006)	0.238*** (0.006)	0.222*** (0.006)	0.191*** (0.008)
Aged 45-54	0.072*** (0.015)	0.116*** (0.011)	0.179*** (0.009)	0.246*** (0.008)	0.298*** (0.007)	0.325*** (0.007)	0.343*** (0.007)	0.337*** (0.007)	0.330*** (0.009)
Aged 55-65	0.030 (0.017)	0.096*** (0.012)	0.160*** (0.010)	0.230*** (0.009)	0.289*** (0.008)	0.320*** (0.008)	0.345*** (0.008)	0.343*** (0.009)	0.350*** (0.011)
Numeracy above median	0.035* (0.015)	0.069*** (0.011)	0.080*** (0.009)	0.081*** (0.008)	0.087*** (0.007)	0.101*** (0.007)	0.118*** (0.007)	0.143*** (0.008)	0.157*** (0.010)
Numeracy above median * Female	0.054** (0.020)	0.034* (0.014)	0.027* (0.012)	0.016 (0.010)	0.018 (0.010)	0.001 (0.009)	-0.019* (0.009)	-0.064*** (0.010)	-0.104*** (0.013)
Education levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full-time indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102567	102567	102567	102567	102567	102567	102567	102567	102567

Notes: Corresponding table for figure B.7 (C). Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.6: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.135*** (0.022)	-0.127*** (0.016)	-0.146*** (0.014)	-0.127*** (0.012)	-0.125*** (0.011)	-0.108*** (0.010)	-0.094*** (0.010)	-0.066*** (0.011)	-0.051*** (0.014)
Aged 30-44	0.099*** (0.015)	0.116*** (0.011)	0.160*** (0.009)	0.194*** (0.008)	0.213*** (0.008)	0.211*** (0.007)	0.209*** (0.007)	0.192*** (0.007)	0.157*** (0.009)
Aged 45-54	0.068*** (0.017)	0.099*** (0.012)	0.160*** (0.010)	0.221*** (0.009)	0.264*** (0.008)	0.289*** (0.008)	0.306*** (0.008)	0.298*** (0.008)	0.285*** (0.010)
Aged 55-65	0.025 (0.019)	0.077*** (0.014)	0.140*** (0.011)	0.203*** (0.010)	0.252*** (0.009)	0.282*** (0.009)	0.305*** (0.009)	0.300*** (0.009)	0.300*** (0.012)
Numeracy above median	0.035* (0.015)	0.071*** (0.011)	0.081*** (0.009)	0.082*** (0.008)	0.088*** (0.007)	0.102*** (0.007)	0.119*** (0.007)	0.145*** (0.008)	0.159*** (0.010)
Numeracy above median * Female	0.050* (0.020)	0.029* (0.014)	0.024* (0.012)	0.013 (0.010)	0.016 (0.010)	-0.001 (0.009)	-0.022* (0.009)	-0.068*** (0.010)	-0.111*** (0.013)
Children	0.050*** (0.015)	0.076*** (0.011)	0.067*** (0.010)	0.072*** (0.008)	0.088*** (0.008)	0.091*** (0.008)	0.099*** (0.008)	0.116*** (0.008)	0.146*** (0.011)
Children × Female	-0.094*** (0.020)	-0.107*** (0.015)	-0.081*** (0.013)	-0.070*** (0.011)	-0.075*** (0.011)	-0.075*** (0.010)	-0.086*** (0.010)	-0.116*** (0.011)	-0.161*** (0.014)
Education levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full-time indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102506	102506	102506	102506	102506	102506	102506	102506	102506

Notes: Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.7: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.061* (0.026)	-0.034 (0.018)	-0.062*** (0.016)	-0.046*** (0.013)	-0.051*** (0.013)	-0.058*** (0.012)	-0.052*** (0.012)	-0.039** (0.013)	-0.020 (0.016)
Aged 30-44	0.160*** (0.016)	0.173*** (0.013)	0.216*** (0.011)	0.233*** (0.009)	0.277*** (0.009)	0.281*** (0.009)	0.307*** (0.009)	0.320*** (0.011)	0.286*** (0.014)
Aged 45-54	0.098*** (0.024)	0.110*** (0.018)	0.186*** (0.015)	0.231*** (0.012)	0.309*** (0.013)	0.353*** (0.013)	0.384*** (0.014)	0.452*** (0.017)	0.476*** (0.023)
Aged 55-65	0.046 (0.032)	0.118*** (0.022)	0.190*** (0.019)	0.243*** (0.016)	0.292*** (0.017)	0.341*** (0.018)	0.383*** (0.020)	0.439*** (0.024)	0.519*** (0.034)
Numeracy above median	0.182*** (0.022)	0.220*** (0.016)	0.203*** (0.014)	0.201*** (0.011)	0.214*** (0.011)	0.209*** (0.011)	0.227*** (0.011)	0.256*** (0.013)	0.257*** (0.016)
Numeracy above median * Female	0.040 (0.031)	-0.010 (0.023)	0.014 (0.020)	-0.001 (0.016)	-0.000 (0.017)	0.012 (0.016)	0.006 (0.016)	-0.023 (0.018)	-0.049* (0.023)
Observations	34645	34645	34645	34645	34645	34645	34645	34645	34645

Notes: Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.8: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.196*** (0.019)	-0.208*** (0.013)	-0.222*** (0.011)	-0.229*** (0.010)	-0.198*** (0.009)	-0.167*** (0.008)	-0.136*** (0.008)	-0.116*** (0.008)	-0.097*** (0.009)
Aged 30-44	0.151*** (0.029)	0.154*** (0.020)	0.177*** (0.017)	0.220*** (0.015)	0.225*** (0.013)	0.225*** (0.011)	0.222*** (0.010)	0.205*** (0.010)	0.179*** (0.010)
Aged 45-54	0.100*** (0.030)	0.124*** (0.020)	0.169*** (0.018)	0.240*** (0.015)	0.268*** (0.014)	0.291*** (0.012)	0.301*** (0.011)	0.284*** (0.011)	0.257*** (0.011)
Aged 55-65	0.078* (0.031)	0.115*** (0.021)	0.151*** (0.018)	0.225*** (0.016)	0.263*** (0.014)	0.288*** (0.013)	0.300*** (0.012)	0.294*** (0.012)	0.298*** (0.013)
Numeracy above median	0.201*** (0.017)	0.223*** (0.013)	0.252*** (0.011)	0.266*** (0.010)	0.293*** (0.009)	0.314*** (0.009)	0.350*** (0.009)	0.377*** (0.009)	0.374*** (0.012)
Numeracy above median * Female	0.069** (0.024)	0.058** (0.018)	0.038* (0.015)	0.036** (0.013)	0.006 (0.012)	-0.030** (0.012)	-0.071*** (0.012)	-0.130*** (0.012)	-0.178*** (0.015)
Observations	71489	71489	71489	71489	71489	71489	71489	71489	71489

Notes: Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.9: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.109*** (0.019)	-0.100*** (0.013)	-0.130*** (0.011)	-0.107*** (0.009)	-0.115*** (0.009)	-0.094*** (0.008)	-0.095*** (0.008)	-0.079*** (0.008)	-0.091*** (0.011)
Aged 30-44	0.132*** (0.017)	0.163*** (0.012)	0.205*** (0.010)	0.252*** (0.008)	0.290*** (0.008)	0.294*** (0.008)	0.290*** (0.007)	0.276*** (0.007)	0.241*** (0.009)
Aged 45-54	0.077*** (0.019)	0.145*** (0.013)	0.199*** (0.011)	0.264*** (0.009)	0.325*** (0.009)	0.358*** (0.008)	0.375*** (0.008)	0.368*** (0.009)	0.361*** (0.011)
Aged 55-65	0.061** (0.021)	0.132*** (0.014)	0.188*** (0.012)	0.257*** (0.010)	0.329*** (0.010)	0.367*** (0.010)	0.390*** (0.010)	0.389*** (0.010)	0.397*** (0.014)
Numeracy above median	0.192*** (0.019)	0.224*** (0.013)	0.219*** (0.011)	0.229*** (0.010)	0.252*** (0.009)	0.275*** (0.009)	0.295*** (0.009)	0.332*** (0.010)	0.365*** (0.014)
Numeracy above median * Female	0.046 (0.025)	0.028 (0.017)	0.022 (0.014)	0.006 (0.012)	0.009 (0.012)	-0.008 (0.011)	-0.026* (0.012)	-0.082*** (0.013)	-0.136*** (0.017)
Observations	76961	76961	76961	76961	76961	76961	76961	76961	76961

Notes: Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.

Table B.10: Relationship Gender Skill and Gender Pay Gap (Quantiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.409*** (0.050)	-0.351*** (0.034)	-0.238*** (0.023)	-0.215*** (0.021)	-0.193*** (0.018)	-0.133*** (0.016)	-0.094*** (0.016)	-0.072*** (0.016)	-0.044** (0.015)
Aged 30-44	0.153*** (0.024)	0.195*** (0.020)	0.243*** (0.017)	0.294*** (0.015)	0.291*** (0.013)	0.296*** (0.012)	0.295*** (0.012)	0.278*** (0.012)	0.203*** (0.012)
Aged 45-54	0.093*** (0.026)	0.142*** (0.023)	0.240*** (0.019)	0.344*** (0.016)	0.363*** (0.014)	0.383*** (0.013)	0.387*** (0.013)	0.381*** (0.014)	0.325*** (0.015)
Aged 55-65	0.040 (0.032)	0.140*** (0.026)	0.191*** (0.021)	0.294*** (0.018)	0.315*** (0.016)	0.348*** (0.016)	0.377*** (0.016)	0.379*** (0.017)	0.348*** (0.019)
Numeracy above median	0.202*** (0.021)	0.222*** (0.018)	0.216*** (0.014)	0.226*** (0.013)	0.220*** (0.011)	0.245*** (0.011)	0.288*** (0.011)	0.302*** (0.012)	0.246*** (0.013)
Numeracy above median * Female	0.274*** (0.056)	0.202*** (0.040)	0.102*** (0.029)	0.068** (0.026)	0.050* (0.023)	-0.008 (0.021)	-0.051* (0.021)	-0.068** (0.022)	-0.097*** (0.022)
Observations	26496	26496	26496	26496	26496	26496	26496	26496	26496

Notes: Dependent Variable: (log) trimmed gross hourly wages (ppp-adjusted). Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Numeracy skill measures are standardized at the country level using sampling probabilities. Unconditional quantile regression with controls for education, field of study, occupation, a full-time indicator and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and respective controls. Data source: PIAAC international PUF 2012.