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ABSTRACT

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

While gender differences in labor force participation and wages have been studied extensively, gender gaps in cognitive skills among adults are not yet well understood. Using the PIAAC dataset, this paper presents novel findings on cognitive skill distributions by gender across 34 countries. Despite increasing educational equality, inequalities in numeracy skills favoring men compared to women are pervasive. These skill differences account for a sizable part of the gender wage gap. Furthermore, there are larger disadvantages for women at the top of the wage distribution, which are complemented by lower returns to skills compared to men. We also find that these numeracy-wage patterns are especially pronounced for parents and for those with the highest degree in a non-STEM field of study.

JEL Classification: I24, J16, J24

Keywords: gender wage gap, skills, numeracy, PIAAC

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1. Introduction

Within economics, there has been much work on cognitive skills as a measure of educational success and as predictors of labor market outcomes. While the measurement of such skills among children and adolescents has been facilitated by the introduction of standardized tests within and across countries, cognitive skills among adults have been harder to study. This has in part been caused by the lack of internationally comparable measures of adult cognitive abilities. The OECD-administered PIAAC survey provides a solution to this missing data problem when studying adult skills. It contains measures of different cognitive skills as well as a rich set of background characteristics for adults aged 16-65 across 37 countries. This allows for a detailed assessment of these skills on a broad set of individuals from different backgrounds.[1]

Getting a better understanding of the cognitive skills of adults is important for several reasons. On the one hand, they can help us understand how early-life knowledge transmits into adulthood. On the other hand, they are related to the puzzle of gender wage gaps among adults, and can provide guidance to evaluate the potential of different types of interventions. Despite recent convergence of labor market outcomes of men and women in many advanced economies, there are still important areas of individuals' lives that contribute to the remaining gender differences, such as parenthood and differences in educational pathways (Goldin, 2014; Bertrand, 2020). Gender differences in labor-market relevant skills might both be an additional factor contributing to these remaining differences, but might also operate through the channels identified in the literature that impede full gender convergence on the labor market (Adda et al., 2017).

In this paper, we exploit the richness of the PIAAC dataset to investigate gender differences in numeracy skills among adults. First, we describe our dataset (Section 2) and then document average gender gaps in numeracy skills across countries and highlight the importance of studying these gaps from a distributional perspective (Section 3). Second, we study the relationship between numeracy skills and wages and highlight the

[1]We use 34 out of the 35 countries with publicly available data in our analyses as described in Data Appendix A.

relevance of numeracy skills in accounting for parts of wage levels and gaps beyond past wages (Section 4). Lastly, we delve deeper into gender numeracy gaps themselves and look at heterogeneity in these gaps along the dimensions most commonly identified in the literature to have an impact on gender gaps in other labor market outcomes (Section 5). To strengthen the argument of the resulting patterns in our cross-sectional setting, we use the German extension of the PIAAC dataset where a short panel of skills for the surveyed adults is available.

This paper delivers five stylized facts, which are intended to open up areas of future research to enhance our understanding of the determinants and consequences of gender gaps in cognitive skills across adulthood. First, we find that despite recent improvements in educational equality in younger cohorts, important differences in skills among adult men and women persist. In most countries we study, men have higher average numeracy skills than women. These gaps in numeracy skills are sizable and cannot be fully explained by commonly used characteristics as well as educational and occupational variables. On the contrary, average gaps tend to increase when accounting for educational decisions, which is in line with the current literature highlighting how women are catching up especially in higher education. Secondly, we confirm that individual numeracy skills are important predictors of wages in a contemporaneous cross-country regression specification. In addition, we use the short German panel of the PIAAC dataset (where the same individuals were surveyed three years apart, in 2012 and 2015) to show that numeracy skills predict current wages even when one controls for past wages and a series of indicators of past decisions.

We derive two further stylized facts from the analysis of this dataset by investigating adult numeracy skills along the joint hourly wage distribution. Gender gaps in numeracy skills in favor of men are much more pronounced at the two top deciles of the wage distribution. No numeracy gaps can be observed in the middle part of the distribution whereas they are visible but relatively smaller in the bottom half of the distribution. Additionally, the share of women is highest in the bottom wage decile and steadily decreases towards the top decile. Furthermore, analyzing wage *returns* to numeracy skills along the wage distribution reveals that there are large differences in returns to higher numeracy skills at the top of the wage distribution, again favoring men. Instead, returns do not differ in the middle part and are even higher for women in the lower half of the wage distribution.

Lastly, we investigate the extent to which these differences depend on parental status and the field of study of individuals. Gaps in numeracy skills at the top of the wage distribution are especially pronounced for parents and those who have completed their highest degree in a non-STEM field of study. Among individuals with children, women are under-represented at the top of the wage distribution, and over-represented at the bottom. Consistently, the difference in *returns* to higher numeracy skills is barely visible for individuals without children, and more evident for individuals with non-STEM fields of study compared to STEM. When decomposing the numeracy gaps along the distribution of numeracy skills using a RIF decomposition (a Kitagawa–Oaxaca–Blinder framework adapted to distributional analyses, roughly speaking), children and fields of study also play a prominent role: they increasingly account for differences in numeracy skills when moving towards the top of the skill distribution. The importance of children in the unexplained part of the decomposition along the entire numeracy distribution links differences in numeracy skills to differential returns to having children for men and women. Instead, country- and cohort-specific institutional features cannot be easily reconciled with the observed patterns. This last stylized fact relates to results from the literature trying to explain gender gaps in wages and working hours. The decisions individuals take about their fields of study and their fertility are hence not only important for explaining these immediately visible labor-market outcomes, but are also connected to our measure of skills of the respective individuals.

This paper contributes to three strands of the existing literature. First, there is a rather established literature studying gender differences in cognitive skills as a measure of education that has almost exclusively focused on children and adolescents. A sizable part of this literature has looked at gender differences in math skills during compulsory schooling (e.g. Hyde et al. (2008) for the US and Contini et al. (2017) for Italy). Gender gaps in favor of boys are found to be especially prominent at the top of the respective skill distribution (Ellison and Swanson, 2010; Robinson and Lubienski, 2011; Contini et al., 2017) or even at both tails of the distribution with males being over-represented at the top and the bottom of the math skill distribution in the US (Autor et al., 2020). We contribute to this literature by focusing on adults whose cognitive skills have largely remained understudied. Two papers that also use PIAAC data to study adult cognitive skills: Rebollo-Sanz and De la Rica (2020) focus on average differences in cognitive skills and Christl and Köppl-Turyna (2020) document gender differences in skills, task and skill matching of workers, and the impact of these factors on the gender wage gap using quantile regressions on Austrian data.[2] Our paper extends this distributional approach to the cross-country PIAAC sample, and additionally delves into potential channels of the observed differences in numeracy skills and their wage returns.

A related and large strand of literature provides ample evidence on gender differences in labor market outcomes, especially in the highest-paid occupations. Albrecht et al. (2003) played an important role in the diffusion of the concept of 'glass ceilings' in the context of gender differences in the labor 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. Blau and Kahn (2017) show that the decrease in the gender wage gap over the last decades in the US was 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 (math in high school), 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

[2] Instead, Pető and Reizer (2021) and Kawaguchi and Toriyabe (2022) focus on the role of skill use at work for explaining gender gaps in labor market outcomes. Pető and Reizer (2021) show that even within the same occupation, women use their cognitive skills less than men. This is especially true for women living in partnerships for whom the hours worked or spent on housework seem to be an important channel of the skill-use imbalance. Kawaguchi and Toriyabe (2022) also show that skill use at work can explain part of the gender wage gap.

school. The literature also investigates possible explanations of glass ceiling effects across countries. For example, Petrongolo and Ronchi (2020) focus on the role of technological change and the increase in service jobs to explain the labor market performance of men and women. This paper adds to this literature by shifting the focus to cognitive skills used on the labor market. Using previously unavailable, internationally comparable measures of numeracy skills paired with a rich set of background characteristics and other labor market outcomes, we provide a detailed distributional analysis of numeracy skills as a potential labor market outcome as well as in their relationship with other labor market outcomes.

Lastly, we contribute to the literature exploring wage returns to cognitive skills. Bacolod and Blum (2010) document an increase in the labor-market returns to cognitive skills and a corresponding decrease in the returns to motor skills in the US. This may have benefited women, since women tend to sort into occupations requiring mostly cognitive skills, 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.[3] Hanushek et al. (2015) investigate the returns to cognitive skills using PIAAC data, and document that returns to cognitive skills are on average insignificantly different for males and females in the group of countries they examine. Again, this stresses the importance of studying gender differences in skills in more depth, in order to reconcile evidence from the glass ceiling literature with the lack of differential *average* returns to skills between men and women.

[3]This literature is in turn related to the work on skill depreciation. Edin and Gustavsson (2008) use Swedish administrative data to document 'economically important' depreciation of general skills after work interruptions. Ortego-Marti (2017) shows that the rate of skill depreciation varies across occupations and industries, and in particular hits those occupations that require more skills. Most recently, Dinerstein et al. (2022) document skill depreciation among teachers in Greece waiting for central assignment to a teaching position after finishing their university degree.

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. PIAAC delivers internationally comparable measures of adult competencies, similarly to what the PISA study does for 15-year-old adolescents. The study focuses on the necessary cognitive skills for advancing at work and participating in society, with the main focus on numeracy[4] and literacy[5] skills. Additionally, some of the participating countries conducted tests on problem-solving in technology-rich environments.[6] The measurement of skills is based on assessments, i.e. tests including a series of questions for each particular domain. Each skill is measured on a 500-point scale.[7] 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 more likely to be comparable across countries.

In addition to the skill measures, PIAAC gathers information on a wide set of socio-economic characteristics and labor market covariates of individuals. In particular, it includes educational attainment and field of study, current work status, occupation, wages and working time, labor market history etc. The richness of background information is an important advantage of this dataset that facilitates a thorough analysis of the factors influencing an individual's skills.[8] The survey was initially conducted in August 2011 to March 2012 in OECD countries. In its second round (April 2014 to March 2015),

[4]Numeracy is defined as *the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life.* A numeracy test can include understanding of a time series on birth rates or understanding different temperature measurement scales.

[5]Literacy is defined as *the ability to understand, evaluate, use, and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential.* For instance, a test on literacy includes a list of pre-school rules and a question on their comprehension.

[6]Sample questions can be found at https://www.oecd.org/skills/piaac/samplequestionsandquestionnaire.htm, last accessed on November 3, 2022.

[7]It 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). For example, Griselda (2022) shows that a substantial part of the gender gap in math performance in PISA standardized tests can be attributed to gender differences in responding to multiple choice questions.

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

PIAAC was carried out in nine additional countries, including new OECD members and a few non-OECD countries. The third round in 2017 added five more countries as well as a second assessment of adults in the United States.[9] In our study, we mostly use information on the 30 countries that provide information on both skills and wages. Table B.1 lists the countries entering our analysis and the sample sizes at our disposal.[10] As we do not focus on international comparisons, we standardize test scores within each country to achieve a mean of zero and a variance equal to one (see also Data Appendix A). The only exceptions to this are Figures 1, B.1, B.2, and B.3 where we show international differences in skill levels. There, the respective skill measure is standardized across the entire country sample.

We acknowledge that the cross-sectional nature of our data source restricts 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 are unfortunately too small to conduct thorough analyses of individuals characteristics. Second, the time span of the dataset covers only three years (from 2012 to 2015), which limits the variation in skill development we can observe. Nonetheless, we use this extension for some selected additional analyses that provide a few useful insights into skill accumulation, bearing in mind that these findings cannot necessarily be generalized for other countries of the international PIAAC sample.

3. Numeracy Skills of Men and Women

We begin by illustrating some cross-country evidence on gender skill gaps. 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. We differentiate

[9]The full list of participating countries and the survey schedule can be found at https://www.oecd.org/skills/piaac/.

[10]For Australia and Indonesia, no Public Use Files are provided on the OECD website. From the remaining 35 out of 37 participating countries, we use all countries except Russia where the dataset is not representative (see Data Appendix A).

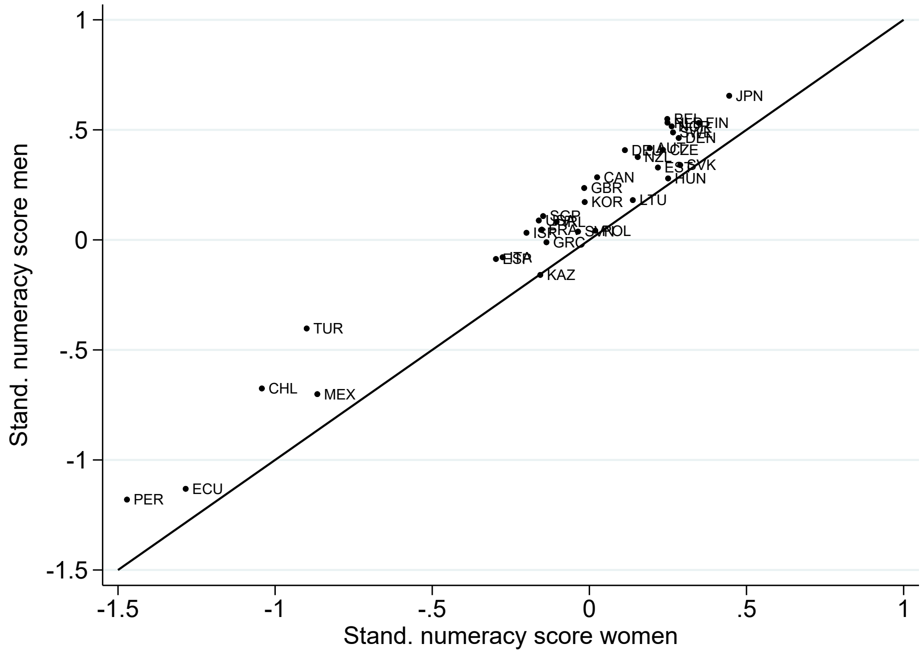
between (a) all individuals and (b) those with non-missing wages, since we often present joint analyses of wages and numeracy levels in later chapters. Both graphs contain a 45-degree line, where test scores would lie in case of equality between genders. Numeracy skills are standardized across the entire sample to reflect differences in numeracy levels between countries.

In all countries of the PIAAC sample, men on average have higher numeracy scores than women such that the resulting data cloud lies entirely above the 45-degree line (Figure 1a). In the sub-sample with non-missing wages (Figure 1b), the picture is very similar with most data points being above the 45-degree line. For some countries, the respective data points are closer or on the 45-degree line, which probably reflects positive selection into the labor market. Comparing panel (a) and panel (b) of Figure 1 suggests that lower labor market participation of women is associated with lower numeracy skills.[11]

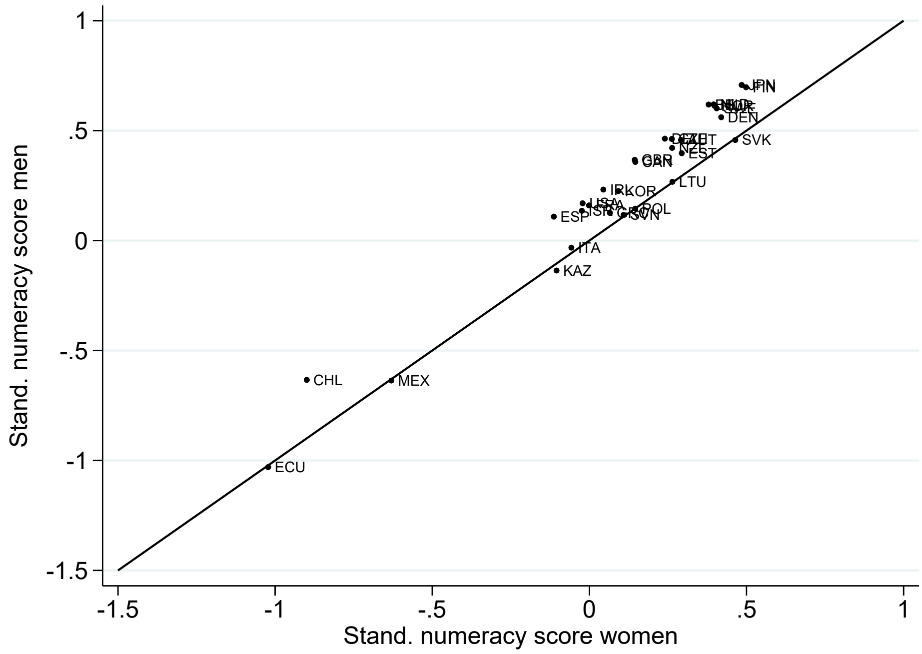
To get a better sense of the magnitude of these average gender gaps in numeracy scores across countries, we also show them in regression form. Table 1 presents a cross-country regression of standardized numeracy scores on a female dummy and country fixed effects. Each column then adds a relevant control which will also be used in later parts of this paper to help explain gender gaps in numeracy scores. Overall, gender gaps in numeracy scores in favor of men are large and persistent. Furthermore, we can see from Column (3) that controlling for an individual's education level actually increases the gender numeracy gap which is in line with the recent literature showing that women actually have surpassed men in terms of education levels. In turn, occupations and fields of study help explaining parts of the gender gap in numeracy scores (Columns 4-6). Lastly, Column 7 adds a variable indicating how much individuals use numeracy skills during their work (self-reported). Even though this variable reduces the gender numeracy gap, the gap is far from disappearing. This piece of evidence already hints at some individual characteristics, choices and constraints that might be relevant for the emergence and

[11] The corresponding within-country gender gaps can be found in Figure B.1. For the purpose of comparison, Figures B.2 and B.3 in the appendix depict equivalent data clouds for literacy and problem-solving. These figures reveal that gender disparity in literacy is much less pronounced and that there is a range of countries where women on average have higher literacy scores than men. Scores for problem-solving resemble the distribution of numeracy scores more closely, both for all adults and for employed individuals only.

Figure 1: Gender-Specific Numeracy Scores by Country



(a) All individuals



(b) Non-missing wages

Notes: Standardized numeracy scores for men and women aged 20 to 65 by country. Standardization across all countries 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 (a; 202,633 individuals) and non-missing wages (b; 99,793 individuals). Data source: PIAAC international PUF 2012.

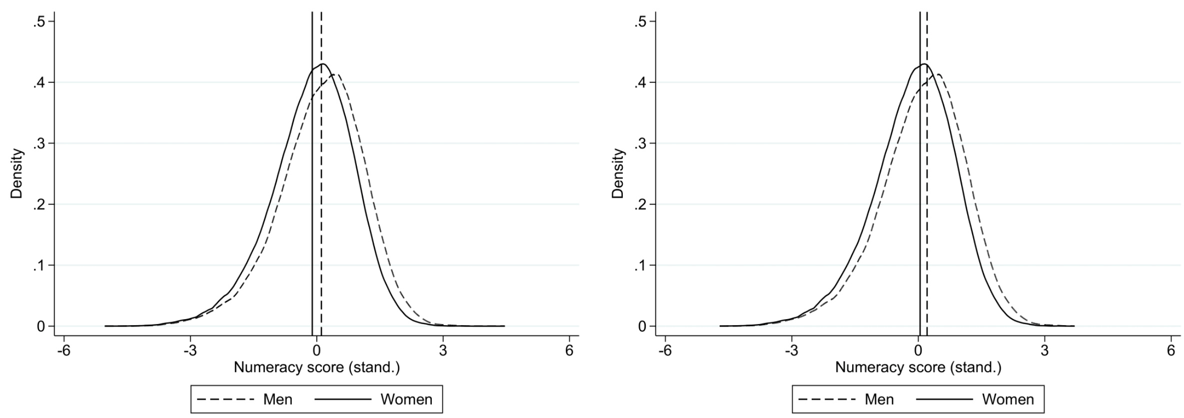
persistence of gender numeracy gaps, but also shows that none of them will most likely be able to explain the entire gap.

Table 1: Gender Gaps in Numeracy Scores Across Countries

	Outcome: Numeracy Score (stand.)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.216***	-0.210***	-0.228***	-0.211***	-0.202***	-0.200***	-0.196***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Age groups		Yes	Yes	Yes	Yes	Yes	Yes
Educational categories			Yes	Yes	Yes	Yes	Yes
Field of study				Yes	Yes	Yes	Yes
Occupational categories					Yes	Yes	Yes
Full-time indicator						Yes	Yes
Numeracy at work							Yes
Observations	202633	202633	202503	197015	136533	136017	109203
R^2	0.012	0.049	0.239	0.255	0.269	0.269	0.249

Notes: Dependent Variable: standardized numeracy scores. Least squares regression with country fixed effects, weighted by individual sampling probability. Estimation sample excludes all observations with missing values for the respective control variables. Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent. Data source: PIAAC international PUF 2012.

Figure 2: Numeracy Score Distributions of Men and Women



(a) All individuals (b) Non-missing wages

Notes: Standardized numeracy scores for men and women aged 20 to 65. Standardization by country uses individuals' sampling probability. Vertical lines represent the respective means for women and men. Sample contains all individuals with non-missing numeracy scores (a; 202,633 individuals) and non-missing wages (b; 99,793 individuals). Data source: PIAAC international PUF 2012.

Focusing on mean test scores only, may lead to an incomplete picture of men's advantage in numeracy. In fact, Figure 2 (a) and Figure 2 (b) show that the distributions of numeracy scores of men and women across countries substantially overlap, implying higher heterogeneity of test scores within gender than between men and women. Figure B.4 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.

In the following analyses, we often group numeracy skills into two categories: above the country-specific median and below. Table 2 shows 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).[12] We present descriptive statistics both for all survey participants (Columns 1-4), and those with non-missing wages (Columns 5-8). Among all participants, the proportion of men in the low-numeracy group is 45 percent, whereas it is nine 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 age groups does not show a distinctive gender pattern.

A more distinctive pattern can be seen for respondents who have children. In the low-numeracy group, 68 percent of men and 80 percent of women have children, whereas in the high-numeracy group the share of respondents with children is six percentage points lower for men and twelve 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 prevalent among the low-numeracy group: in both numeracy-level groups, more women than men have tertiary education. This 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 in particular 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.[13]

[12]The underlying distribution uses all individuals with non-missing numeracy scores without any further restrictions. The same classification is used in all analyses using numeracy above or below the median, independently of other restrictions applied to the respective samples.

[13]The fields 'Science, mathematics and computing' and 'Engineering, manufacturing and construction'

Table 2: 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share	0.45	0.55	0.54	0.46	0.48	0.52	0.55	0.45
Socio-demographics								
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
Has children	0.68	0.80	0.62	0.68	0.67	0.76	0.64	0.67
Education								
Lower secondary or less	0.37	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	0.50	0.44	0.37
Tertiary	0.14	0.20	0.43	0.50	0.16	0.28	0.47	0.57
Field of study								
General programmes	0.12	0.14	0.13	0.14	0.11	0.13	0.10	0.11
Teacher training and education science	0.02	0.06	0.03	0.10	0.02	0.09	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	0.12	0.09
Engineering, manufacturing and construction	0.27	0.05	0.31	0.07	0.32	0.06	0.34	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
Missing (lower secondary education or less)	0.35	0.34	0.11	0.09	0.27	0.20	0.08	0.05
STEM field of study	0.31	0.08	0.42	0.15	0.36	0.09	0.46	0.15
Occupation								
Armed forces occupations	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00
Managers	0.06	0.04	0.13	0.08	0.04	0.03	0.11	0.07
Professionals	0.06	0.14	0.23	0.31	0.06	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	0.13	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 agricultural, forestry and 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	0.04	0.14	0.02
Plant and machine operators and assemblers	0.17	0.04	0.09	0.02	0.19	0.04	0.10	0.02
Elementary occupations	0.11	0.15	0.04	0.05	0.12	0.15	0.05	0.05
Labor Market								
Share employed	0.73	0.58	0.83	0.72	1.00	1.00	1.00	1.00
Share full-time employed	0.91	0.73	0.91	0.77	0.92	0.74	0.93	0.79
Average wage	2.42	2.36	2.70	2.55	2.42	2.36	2.70	2.55
Wage p10	1.50	1.46	1.76	1.64	1.50	1.46	1.76	1.64
Wage p90	3.19	3.13	3.52	3.34	3.19	3.13	3.52	3.34
Observations	43,008	58,301	51,521	49,803	20,206	24,485	28,601	26,501
Observations (numeracy groups)	101,309		101,324		44,691		55,102	
Observations (availability wages)	202,633				99,793			

Notes: Descriptive statistics for men and women aged 20 to 65 by numeracy levels above or below the country-specific median, using sampling weights. Field of study STEM refers to categories 'Science, mathematics and computing' and 'Engineering, manufacturing and construction'. Sample contains all individuals aged 20 to 65 with non-missing numeracy scores. Data source: PIAAC international PUF 2012.

Furthermore, women choose a STEM field of study less often in both numeracy groups. 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 increases from the low- to the high-numeracy group, both for men (from 73 to 83 percent) and especially for women (from 58 to 72 percent). Among these, the share of full-time workers is around 90 percent for men in both skill groups, whereas it is much lower for women (73 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 widens with numeracy levels and is especially high among high-numeracy top earners. In general, these descriptive statistics demonstrate that numeracy levels are closely linked to labor market activity, wages, the probability of having children, and some fields of study and occupations. Columns 5-8 of Table 2 show that individuals with non-missing wages are much more likely to have high levels of education and have a slightly different age structure, especially among those with below-median numeracy skills.

This section shows that gender disparities in numeracy skills among adults are pervasive and cannot be fully explained by differences in standard labor market characteristics. Beyond these average numeracy gaps, we are particularly interested in distributional analyses due to the large overlap of men's and women's numeracy skill distributions. Our focus on numeracy skills is rooted in their relevance in the labor market. In the following section, we discuss wage returns to numeracy skills.

are classified as STEM.

4. Numeracy and Wages

4.1. Average Returns to Skills

In the following, we explore how numeracy skills are related to wages, and which insights skill gaps can provide on the formation of the gender wage gap. Because of the cross-sectional nature of the data, we observe skills and wages simultaneously.[14] Their relationship could hence go in both directions: 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 to preserve skill levels. Table 3 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 for wages than literacy or problem-solving skills, both when included individually as well as simultaneously. Additionally, Table 3 includes interactions of the respective skill variables with a dummy for being female, showing that *average* returns to skills for men and women cannot be statistically distinguished for numeracy and literacy skills in the specifications where skills enter separately (Columns 4 and 6). This is not the case for problem-solving where returns to skills are higher for women (Column 8). This preserves into the specification where all skills are included simultaneously (Column 9), although 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

Numeracy skill levels do not only explain current wages, but also matter for the evolution of wages over time. Table 4 exploits the panel structure of the German PIAAC-L data

[14] Figure B.5 in the appendix shows the distributions of (log) hourly wages (adjusted by country-specific PPP) of men and women pooled across all countries. 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's over-proportionate engagement in part-time work. This most likely leads both to lower monthly earnings due to reduced working hours as well as to a penalty in hourly wage rates.

Table 3: Returns to Skills: Regression of Log Hourly Wages on Skill Scores

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.149***	-0.179***	-0.166***	-0.165***	-0.176***	-0.175***	-0.168***	-0.170***	-0.160***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Numeracy (Num.)			0.067***	0.069***					0.055***
			(0.002)	(0.003)					(0.007)
Num. * Female				-0.004					-0.024**
				(0.004)					(0.009)
Literacy (Lit.)					0.056***	0.056***			0.018*
					(0.002)	(0.003)			(0.007)
Lit. * Female						-0.001			0.009
						(0.004)			(0.010)
Problem Solving (PS)							0.049***	0.042***	-0.004
							(0.002)	(0.003)	(0.005)
PS * Female								0.016***	0.025***
								(0.004)	(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	99793	96240	96234	96234	96234	96234	71082	71082	71082
R^2	0.455	0.611	0.618	0.618	0.616	0.616	0.611	0.611	0.614

Notes: Dependent Variable: log trimmed gross hourly wages (PPP-adjusted). Wage measures are trimmed and imputed with decile medians if a 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, occupation, and a full-time indicator are included in Columns 2-9. Baseline category for age groups is 20 to 29, the constant is omitted in the output. Sample contains all individuals aged 20 to 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.

by showing the dependence of wages in 2015 on wages and numeracy skills in 2012. Column (1) shows the raw gender gap, Column (2) confirms the existence of a gender wage gap in wages 2015 after controlling for age, education, field of study, occupational groups, and full-time work in 2012. Column (3) reveals a positive dependence of wages in 2015 from wages three years before, and shows that the female dummy indicating the gender wage gap even loses statistical significance. This implies that past wages absorb factors driving the gender wage 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 (4) 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 notably, Column (5) shows that numeracy skills in 2012 have predictive power for wages in 2015 beyond what can be explained by past wages. This highlights the importance of looking at the emergence and development of numeracy skills beyond their importance for wage gaps. Column (6) additionally includes contemporaneous numeracy levels for men and women, which both remain insignificant in the presence of past numeracy and wages. However, the last column in particular shows that past numeracy for men is correlated with a wage premium, which is completely canceled out for women. This implies that higher numeracy levels are associated with higher wage growth, but only for men.

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.6 (A) depicts the result of a Kitagawa–Oaxaca–Blinder decomposition of the gender wage gap into the explained and unexplained parts without considering numeracy levels (left bar) and with 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 wage gap. Figure B.6 (B) performs the same decomposition by country and shows that considering numeracy levels increases the gender wage gap

Table 4: Current Wages, Past Wages and Numeracy Skills

	Outcome: Log Hourly Wages in 2015					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.089***	-0.080**	0.034	-0.055	-0.010	0.003
	(0.025)	(0.026)	(0.120)	(0.030)	(0.119)	(0.118)
Wages (2012)			0.514***		0.492***	0.490***
			(0.038)		(0.038)	(0.038)
Wages (2012) × Female			-0.018		0.004	0.001
			(0.043)		(0.043)	(0.043)
Numeracy (2012)				0.096***	0.058***	0.054**
				(0.020)	(0.017)	(0.019)
Numeracy (2012) × Female				-0.044	-0.034	-0.047
				(0.033)	(0.023)	(0.027)
Numeracy (2015)						0.008
						(0.017)
Numeracy (2015) × Female						0.022
						(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	2006	1827	1734	1827	1734	1734
R^2	0.008	0.283	0.522	0.300	0.528	0.529

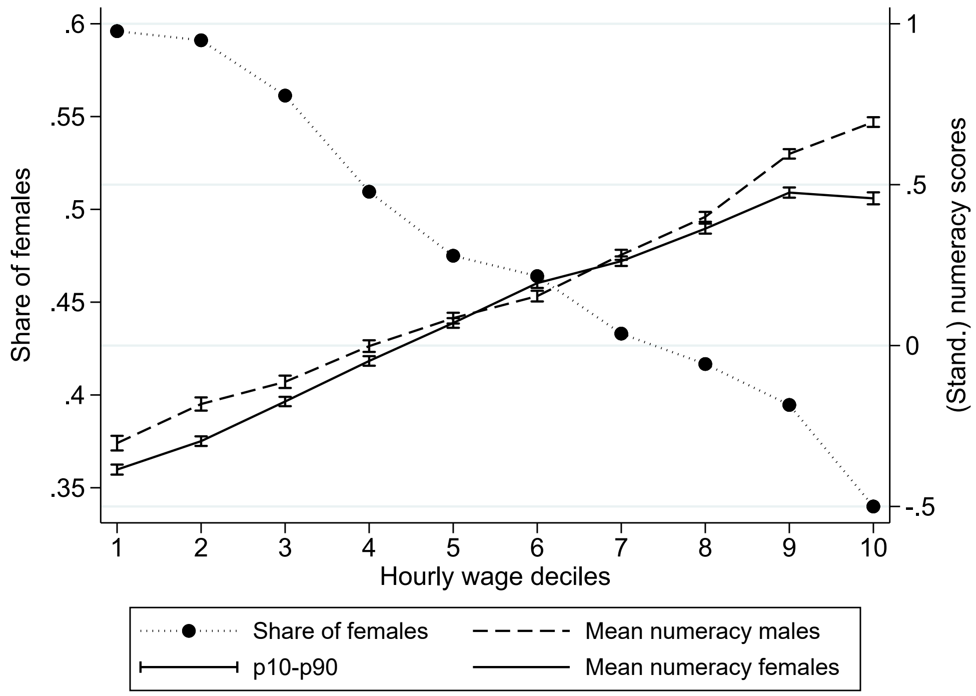
Notes: Dependent variable: log trimmed gross hourly wages in 2015. Least squares regression weighted by individuals' sampling probability. Dummies for education, field of study and occupation as well as a full-time indicator are included in columns 2-6. Baseline category for age groups is 20 to 29, the constant is omitted in the output. Sample contains individuals aged 20 to 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 German SUF 2015 and 2012.

only in few countries (including Japan, Chile, and the Czech Republic), whereas they are a substantial factor for explaining gender wage gaps in most other countries. Again, returns to numeracy do not substantially contribute to the average gender wage gap in most countries.

4.3. Distributions of Numeracy Skills and Wages

Average differences mask important heterogeneity in the gender-specific patterns of skills and wages. We therefore now turn to analyzing the distributional aspects of numeracy gaps between women and men. Figure 3 plots the share of women as well as average numeracy scores for women and men along deciles of the joint hourly wage distribution 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 average numeracy levels being lower for low-wage earners and higher for high-wage earners. However, this simple representation reveals clear gender-specific pattern: men (dashed line) have relatively higher numeracy levels at the bottom and especially at the top of the wage distribution, whereas 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), pointing towards 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 by country uses individuals' sampling probability, deciles are calculated by country. Sample contains all individuals aged 20 to 65 with non-missing wages, i.e. 99,793 individuals. 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 study 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:

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

The dependent variable is the log hourly wage of an individual i living in country c. *Female* is a binary variable equal to one 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).[15] We also include an interaction term of the female dummy and the numeracy level. Thus, $\widehat{\gamma}$ captures the returns to having above-median numeracy skills for men, relative to those with below-median numeracy levels. $\widehat{\delta}$ 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 to 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 ($\widehat{\gamma}$) and for women ($\widehat{\gamma} + \widehat{\delta}$). The figure also depicts the marginal effect for females ($\widehat{\beta} + \widehat{\delta}$) to represent the gender wage gap at the respective decile border.

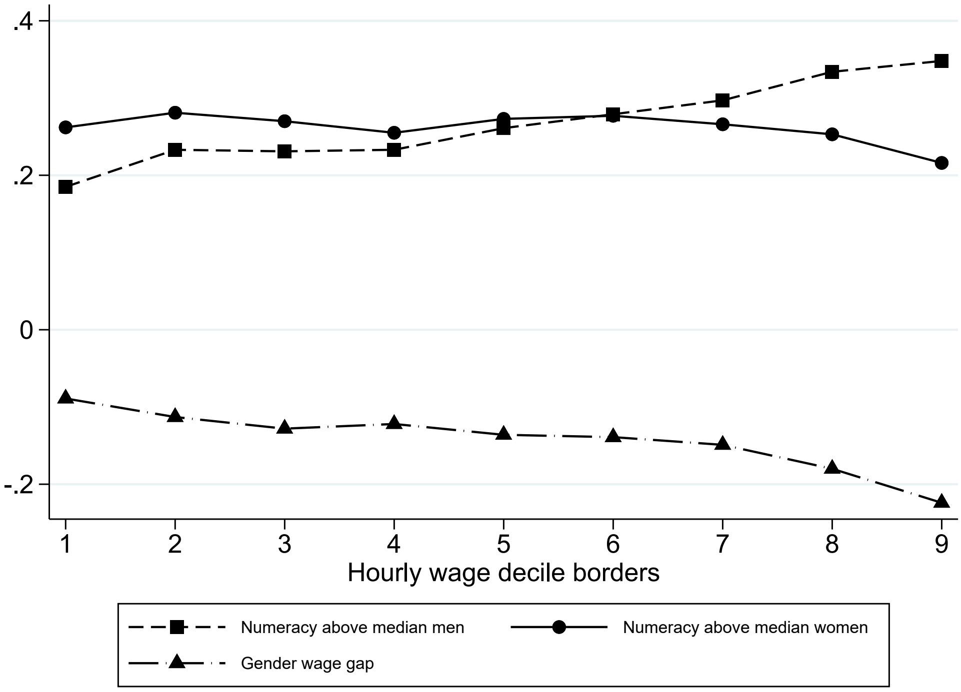
Figure 4 confirms the established empirical fact that the gender wage gap is increasing (i.e. worsening) from the bottom to the top of the wage distribution and is especially pronounced at the top two deciles. The figure also reveals gender-specific patterns in returns to numeracy: below the median hourly wage, returns to high numeracy levels are slightly larger for women than for men. In the middle of the wage distribution, returns to above-median numeracy are roughly equal and for the top two deciles, returns to higher numeracy levels are much higher for men than for women. This is because 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.[16]

Figure B.8 provides the same graph resulting from an estimation of Equation 1

[15]As in Table 2, the median split is performed on all individuals with numeracy scores in the respective country.

[16]Figure B.7 depicts the returns to numeracy for women relative to men by plotting the $\widehat{\delta}$ stemming from a country-wise estimation of Equation 1. With few exceptions, we observe a dominant pattern of returns to 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.

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 ($\widehat{\gamma}$, dashed lines with squares) and for women ($\widehat{\gamma}+\widehat{\delta}$, solid lines with circles) as described above. The dash-dotted line with triangles plots the marginal effect for females ($\widehat{\beta}+\widehat{\delta}$) as described above. Corresponding coefficients can be found in Table B.2. Numeracy scores are standardized by country using individuals' sampling probability. Sample contains all individuals aged 20 to 65 with non-missing wages and numeracy scores, i.e. 99,793 individuals. Data source: PIAAC international PUF 2012.

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. The 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 to other, unobservable factors related to skills (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 as the influence of children, in Table B.6, we add an indicator for having children as well as its interaction with the female dummy to the extended specification of Equation 1. We observe positive returns to children for men that increase from the lower to the upper deciles of the wage distribution. For women, this positive return is entirely canceled out. This points towards distinctively different wage settings for fathers and mothers, even after controlling for their education, occupation, and working time schedule.

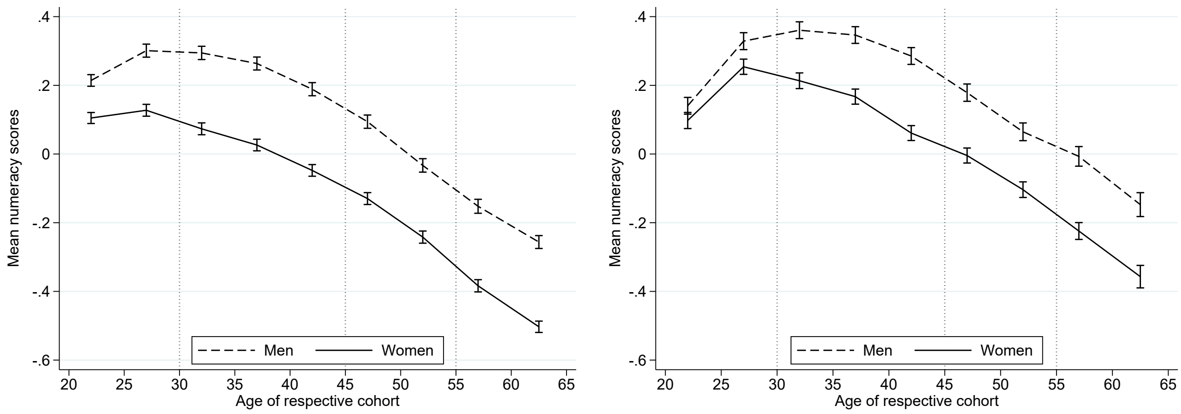
In this section, we have explored the connection of adult numeracy skills and their contemporaneous and past wages. Numeracy skills are strong predictors of wages, both in contemporaneous regressions as well as in the short German panel including past wages and indicators. The patterns we observe speak to the glass ceiling effect for wages, which has been observed and investigated in the literature. Women have both lower average numeracy skills as well as lower returns to higher numeracy skills at the top of the wage distribution. They are also highly under-represented in this part of the distribution.

5. Possible Drivers of Gender Skill Differences

The evidence presented above reveals that women have a disadvantage due to both lower numeracy levels and lower wage 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 women's current or past circumstances compared to men, which are likely to be a complex combination of choices and constraints. In the following, we provide empirical evidence on some of the channels that may explain the differences in observed numeracy levels. These differences arise from individual choice as well an various external constraints.

Depicting the average numeracy levels for men and women in five-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, mean numeracy scores are higher for men than for women, with the lowest gap for the youngest group. This pattern is especially striking among respondents with non-missing wages. Moreover, for women, numeracy scores peak at ages 25 to 30 and then decrease. Men's numeracy levels are also highest for ages 25 to 30, but then remain at about the same level for the age groups 30 to 35 and 35 to 40 before they decrease for older groups. Hence, gender differences in numeracy skills are not specific to any age, but are instead present across the entire age distribution.

Figure 5: Numeracy Scores, by Age and Gender



(a) All individuals (b) Non-missing wages

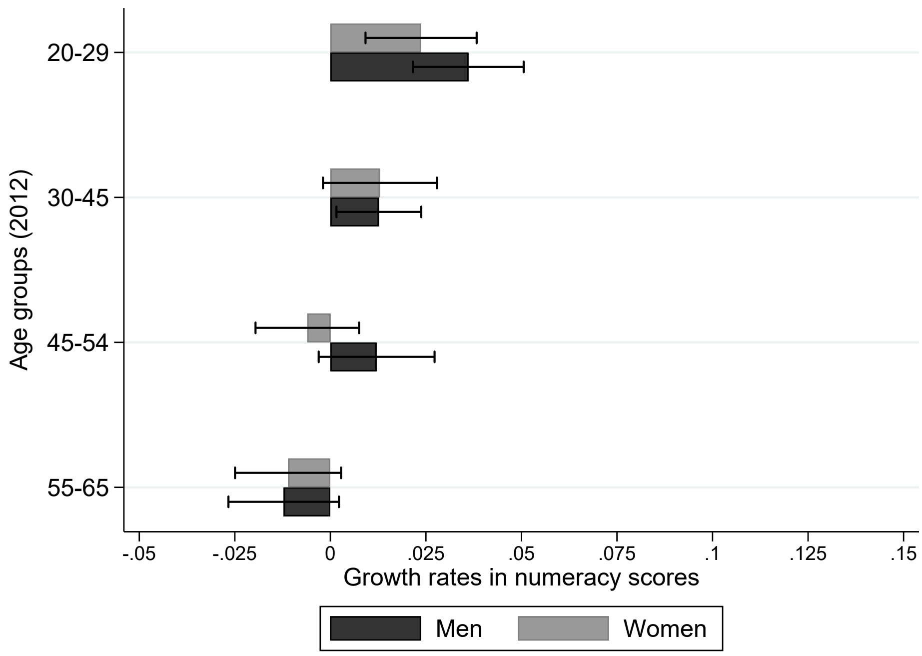
Notes: Mean standardized numeracy scores by age (in five-year intervals) for men and women aged 20 to 65. Confidence intervals for each data point are added, vertical lines represent cut-offs of age groups used in the regressions at ages 30, 45, and 55. Standardization by country uses individuals' sampling probability. Sample contains all individuals with non-missing numeracy scores and age (a; 202,633 individuals) and non-missing wages (b; 99,793 individuals). Data source: PIAAC international PUF 2012.

5.1. Skill Accumulation Using Panel Data

Figure 5 relies on cross-sectional data from respondents of different ages, and therefore does not allow to distinguish between age and cohort effects. 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 a relatively more equal gender distribution of skills among the young can be eradicated over the course of their lives if there is no change in institutional settings for skill accumulation and depreciation.

Using the German panel dataset PIAAC-L, we are able to disentangle these two effects, albeit with a smaller national sample and a short time span. Rebollo-Sanz and De la Rica (2020) mention that age-related gender skill profiles are likely to depend on skill depreciation. With the PIAAC-L data, we can 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 to 29 years old), both men and women improve their numeracy skills over time (i.e. until 2015). Men's skill gains are larger than those of women, though not significantly. In the age group 30 to 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 to 54, women have an insignificant skill loss, whereas men again improve their skills. Among the oldest group aged 55 to 65, we observe a skill loss for both men and women.

Figure 6: Numeracy Score Gains Between 2015 and 2012 in Germany



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. We use the updated 2012 numeracy values from the 2015 survey. Age groups refer to the age reported in 2012. Confidence intervals are added for bars. Sample contains all individuals aged 20 to 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.

Table 5 depicts the dependence of 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. Instead, the interaction term of past numeracy with the female dummy is insignificant. Adding a series of 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 the skill accumulation of women, but not of men (Column 6). In this last specification, the coefficient on the female dummy decreases substantially in size and loses significance.

Table 5: Accumulation of Numeracy Skills over Time

	Outcome: Numeracy Scores in 2015						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.111**	-0.110**	-0.113***	-0.129***	-0.143**	-0.164***	-0.086
	(0.034)	(0.034)	(0.034)	(0.039)	(0.046)	(0.048)	(0.065)
Numeracy (2012)	0.750***	0.750***	0.716***	0.696***	0.644***	0.643***	0.644***
	(0.029)	(0.029)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
Numeracy (2012) × Female	-0.045	-0.045	-0.044	-0.034	0.007	0.011	0.002
	(0.040)	(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			Yes	Yes	Yes	Yes	Yes
Field of study 2012				Yes	Yes	Yes	Yes
Occupational categories 2012					Yes	Yes	Yes
Full-time 2012						Yes	Yes
Observations	2961	2961	2960	2956	2353	2347	2347
R^2	0.502	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 the 2012-2015 sample. 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 suggested by Table B.6, parental status plays an important role for the gender-specific relationship between skills and wages. Figure 7 (A) plots both numeracy scores by gender and shares of women along the hourly wage distribution for individuals with and without children. The numeracy profiles for men and women with and without children respectively are almost overlapping, except at the very top of the wage distribution. In the highest wage deciles, there is a substantial gap between men's and women's average numeracy skills which is more pronounced for individuals with children. In fact, for men, there seems to be no difference in average numeracy skills in the highest decile by parental status. Along the rest of the distribution, childless individuals tend to have higher numeracy skills than those with children. When turning to gender shares within each wage decile, a more differentiated picture emerges for individuals with and without children. Among women and men with children, women are vastly over-represented in low paying jobs and highly under-represented at the top of the wage distribution. This pattern is similar for those without children, but it is less pronounced both at the top and at the bottom of the wage distribution.

Figure 7 (B) presents returns to numeracy skills and the gender wage gap along the wage distribution by parental status. For childless men and women (black lines), the gender gap is much smaller. Also, their returns to numeracy are constant, with minor exemptions for the first and last decile borders. For men with children (gray dashed line), we observe increasing returns to numeracy along wage deciles, whereas the skill returns of women with children (gray solid line) are slightly declining above the median. Together, this suggests a stronger favoritism with respect to skills of fathers compared to mothers.

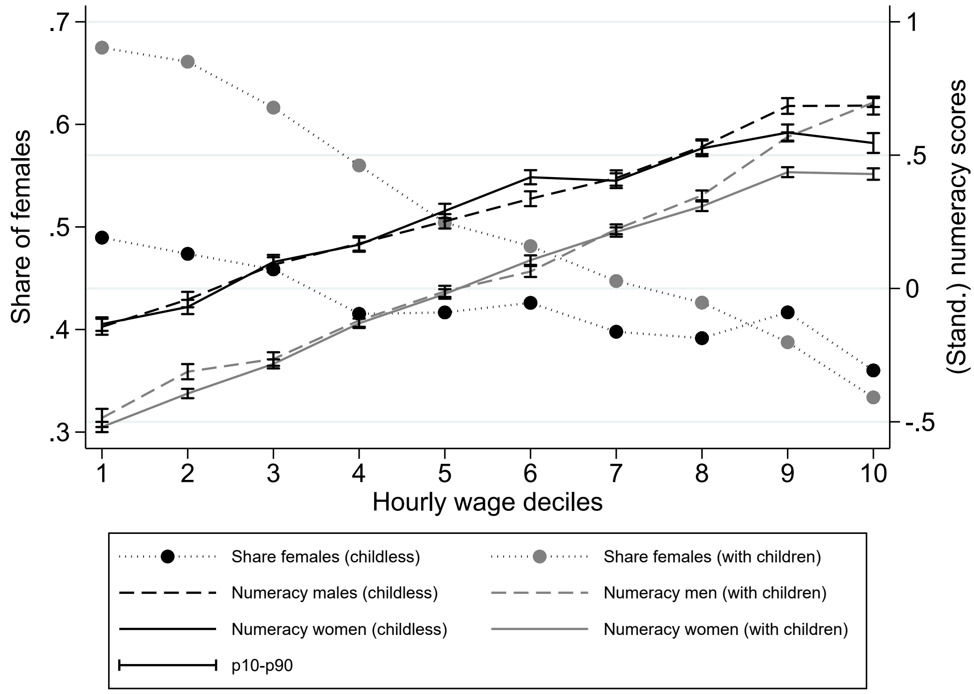
The results from Figure 7 may partly be driven by selectivity into parental status. In order to address this aspect, Figure B.9 (A) presents gender-specific numeracy profiles for men and women depending on the age when they had their first child. It illustrates that particularly women who had their first child at a young age, exhibit lower numeracy levels than men who had their first child at the same age, and also as women who had their first child later in life. Figure B.9 (B) shows the residuals of regressing numeracy on education levels, which highlights an even higher discrepancy by gender and high selectivity on numeracy levels for fertility decisions.

5.3. Heterogeneity by Higher Degrees in STEM

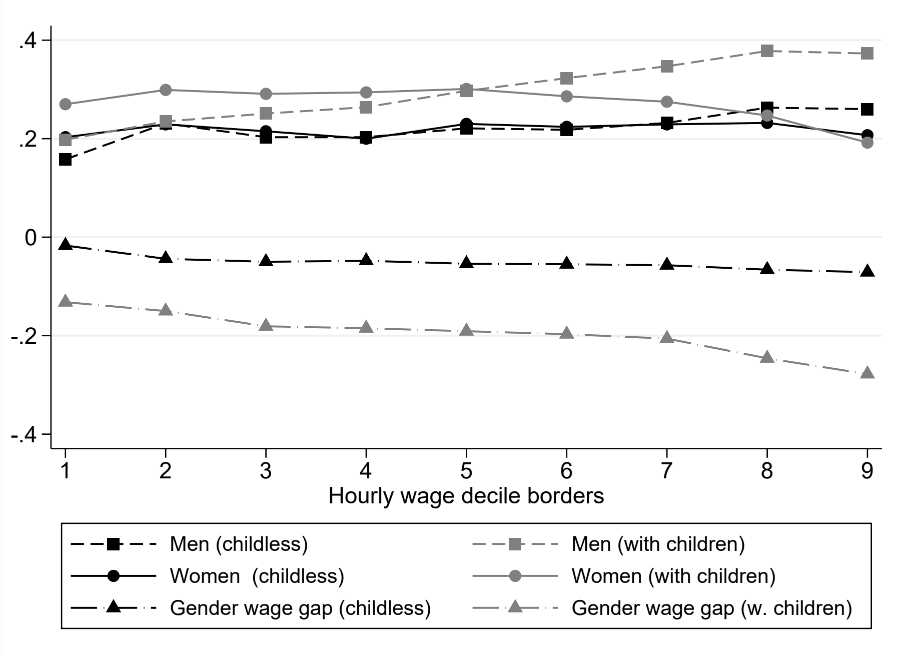
Given that numeracy skills are especially required in STEM-related occupations and women are under-represented in STEM jobs (see e.g. Speer (2023) for the US), we provide heterogeneity analyses by STEM versus non-STEM fields of study (Figure 8) and industries (Figure B.10). Figure 8 (A) again shows numeracy skills along the wage distribution as well as shares of women. Women are highly under-represented in STEM fields of study along the entire wage distribution. Instead, they are over-represented at all deciles for non-STEM fields of study, except at the very top of the wage distribution.

Instead, for numeracy skills, the picture is more differentiated. Individuals with

Figure 7: Parental Status, Numeracy Levels and Wages



(A) Numeracy along the wage distribution, by gender and parental status



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

Notes: Panel A: Weighted shares of females within the respective deciles of hourly wages, and standardized numeracy scores for men and women, by parental status. Standardization by country uses individuals' sampling probability, deciles are calculated by country. Sample contains all individuals aged 20 to 65 with non-missing wages, numeracy scores, and information on children (99,722 individuals). Panel B: Relative returns to above-median numeracy levels for men and women by having children. The dash-dotted lines plot the marginal effect for females. Corresponding coefficients can be found in tables B.7 and B.8. Numeracy scores are standardized by country using individuals' sampling probability. Sample contains all individuals aged 20 to 65 with non-missing wages, numeracy scores, and information on children (99,722 individuals). Data source: PIAAC international PUF 2012.

degrees in non-STEM fields of study generally have lower numeracy skills than those from STEM fields of study. Furthermore, in the non-STEM group there are barely any gender gaps in numeracy skills except at the top of the wage distribution where men outperform women. This pattern is reversed for STEM fields of study where women outperform men in the largest part of the distribution, i.e. from the fourth to the ninth decile. Instead, at the extremes of the wage distribution, men have higher average numeracy skills than women.

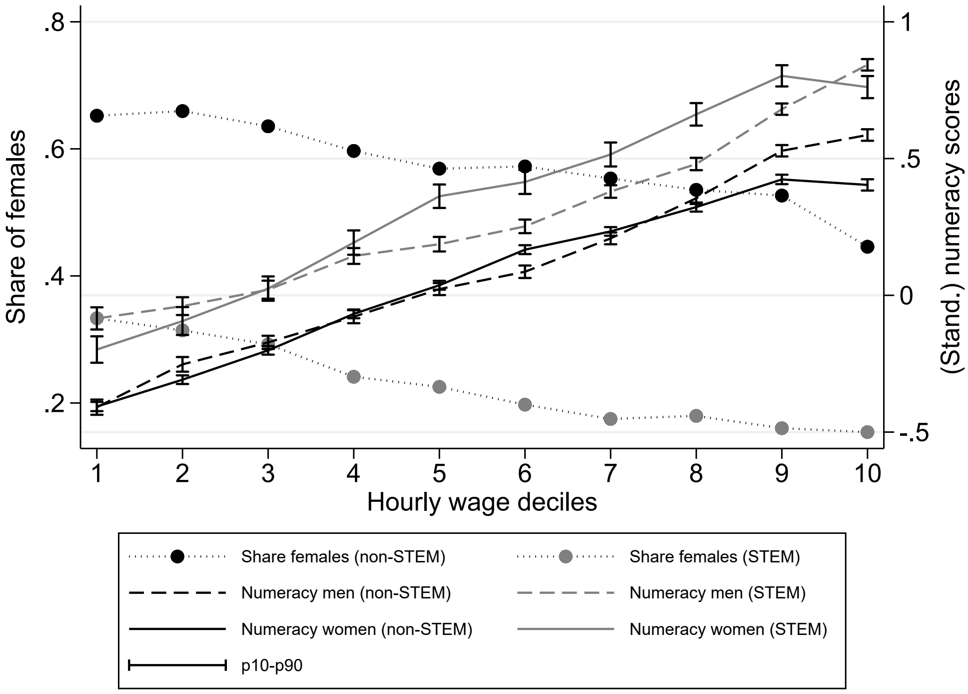
Figure 8 (B) depicts the gender wage gap and returns to skills along the joint hourly wage distribution. The gender wage gap for respondents educated in STEM-related fields of study remains constant over the wage distribution, whereas it increases with higher wages for non-STEM fields of study. Strikingly, we observe that women with education in STEM-related fields have substantially higher returns to their skills in lower wage deciles, pointing towards higher favoritism of women at the bottom of the wage distribution.

Figure B.10 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.10 (A) shows that the numeracy profiles of men and women in STEM and non-STEM industries almost overlap. Figure B.10 (B) also depicts an overlap of profiles of women in STEM and non-STEM industries for respondents from non-STEM fields of study. At the same time, in this sub-figure, numeracy levels of men are higher in STEM and (especially) non-STEM industries. The latter evidence may point towards 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 field of study (as shown in Figure 8) is decisive for numeracy levels, not the current occupation in a particular industry.

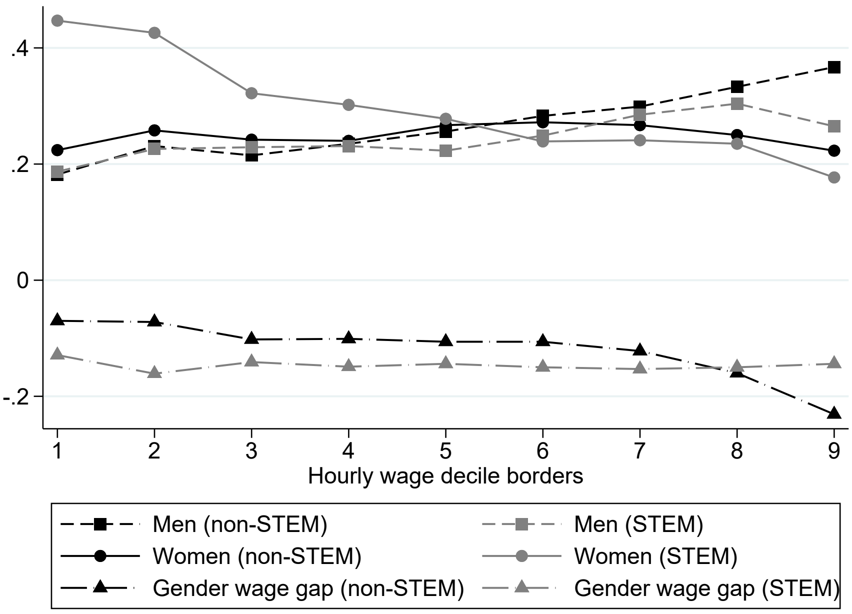
5.4. Norms and Institutions

Country norms regarding the role of women for child care may matter for labor market outcomes. Figure 9 plots country averages for the gender numeracy gap against the percentage of the ISSP-respondents who agree with the statement that 'mothers of

Figure 8: STEM v Non-STEM Field of Study, Numeracy Levels and Wages



(A) Numeracy along the wage distribution, by gender and field of study

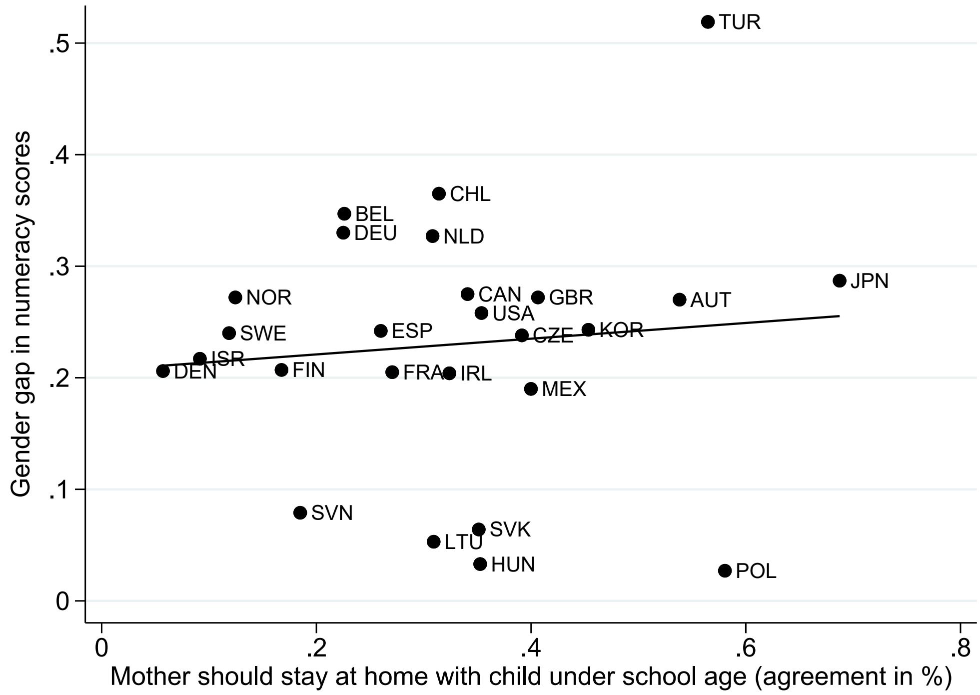


(B) Returns to skills, by gender and field of study

Notes: Panel A: Weighted shares of females within the respective deciles of hourly wages, and standardized numeracy scores for men and women, by field of study. Standardization by country uses individuals' sampling probability, deciles are calculated by country. Sample contains all individuals aged 20 to 65 with non-missing wages, numeracy scores, and field of study (97,094 individuals). Panel B: Relative returns to above-median numeracy levels for men and women by field of study. The dash-dotted lines plot marginal effect for females respectively. Corresponding coefficients can be found in tables B.9 and B.10. Numeracy scores are standardized by country using individuals' sampling probability. Sample contains all individuals aged 20 to 65 with non-missing wages, numeracy scores, and field of study (97,094 individuals). Data source: PIAAC international PUF 2012.

children under school age should stay at home'.[17] No clear pattern can be observed, even though there is a weak positive relationship. It appears crucial to use the variance *within* countries to study these relationships. This has been recently discussed by Moriconi and Rodríguez-Planas (2021), who investigate the role of gender norms on the motherhood employment gaps across 186 regions in 29 countries.

Figure 9: Numeracy and Norms



Notes: Gender wage gap in standardized numeracy scores for men and women aged 20 to 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. The R-squared from a simple regression of gender numeracy gaps on gender norms is 0.27. Sample contains individuals aged 20 to 65 with non-missing numeracy scores from PIAAC and countries with non-missing norms information from ISSP 2012 (26 countries, i.e. 158,987 individuals). Data source: PIAAC international PUF 2012 and data on norms from the 2012 ISSP questionnaire on "Family and Changing Gender Roles" (ISSP Research Group, 2016).

In the following, we reassess 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 future plans. Table 6 starts with a specification in Column (1) that includes only the female dummy. This estimates a raw gender gap for all individuals in the sample who have non-missing numeracy scores and are no first-generation migrants since for the latter we

[17]The International Social Survey Programme (ISSP) on 'Family and Changing Gender Roles' IV was mainly conducted in 2012 among almost 40 countries (ISSP Research Group, 2016).

cannot adequately control for the country-of-origin institutional conditions. The inclusion of age brackets as controls yields virtually the same result (Column 2).

Specification (3) adds the demeaned country-specific unemployment rate in the year the respondent was 15 years old and its interaction with the female dummy, to control for the overall economic conditions in the country at that time. We observe a significant positive correlation of the unemployment rate with the numeracy level for women, but no large change in the gender numeracy gap which corresponds to the coefficient on the female dummy here. Column (4) adds demeaned labor 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.

Specification (5) includes the demeaned version of a proxy for *females in science* that measures the aggregate share of female authors in astrophysics in a country during the years when the respondent was 14 to 16 years old.[18] Although it seems reasonable to include this proxy in such a context since it aims to depict the presence of female role models in science, it neither correlates significantly with numeracy levels in the presence of other controls, nor does it contribute to the gender numeracy gap. Column (6) adds demeaned 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.

Finally, Column (7) shows the results when using control variables on parental education and interactions of the country and the respondents' year of birth 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. Overall, this evidence points towards a relatively small importance of

[18] Our 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.

the institutional factors for the formation of the gender numeracy gap.

Table 6: Initial Labor Market Conditions and Numeracy Scores

	Outcome: Numeracy Scores (stand.)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.209***	-0.209***	-0.214***	-0.227***	-0.227***	-0.220***	-0.201***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.012)	(0.011)	(0.008)
Unemployment rate			0.027	0.354	0.160	0.060	
			(0.239)	(0.318)	(0.376)	(0.363)	
Unemployment rate × Female			0.668***	0.395	0.425	0.171	
			(0.200)	(0.287)	(0.368)	(0.360)	
Female LFP				0.352	0.386	0.431	
				(0.278)	(0.342)	(0.340)	
Female LFP × Female				0.236*	0.259	0.236	
				(0.117)	(0.162)	(0.161)	
Male LFP				-0.169	-0.313	-0.714	
				(0.417)	(0.495)	(0.516)	
Male LFP × Female				-0.512*	-0.577	-0.778	
				(0.226)	(0.439)	(0.430)	
Females in science					0.072	0.078	
					(0.285)	(0.278)	
Females in science × Female					0.231	0.193	
					(0.306)	(0.301)	
Mother educ. intermediary						0.228***	0.204***
						(0.023)	(0.015)
Mother educ. intermediary × Female						0.045	0.060**
						(0.030)	(0.020)
Mother educ. high						0.418***	0.430***
						(0.027)	(0.019)
Mother educ. high × Female						0.052	0.025
						(0.036)	(0.025)
Father educ. intermediary						0.209***	0.217***
						(0.022)	(0.015)
Father educ. intermediary × Female						-0.019	-0.024
						(0.030)	(0.021)
Father educ. high						0.489***	0.465***
						(0.027)	(0.018)
Father educ. high × Female						-0.062	-0.057*
						(0.035)	(0.024)
Aged 30-44		-0.007	-0.010	0.032	0.054	0.028	0.011
		(0.032)	(0.033)	(0.037)	(0.042)	(0.038)	(0.052)
Aged 45-54		-0.063	0.013	0.278	0.308	0.505**	0.089
		(0.073)	(0.106)	(0.167)	(0.169)	(0.159)	(0.141)
Aged 55-65		-0.631***	-0.578***	0.094	0.123	0.508**	-0.303**
		(0.163)	(0.145)	(0.179)	(0.182)	(0.173)	(0.095)
Observations	83767	83767	74272	56905	36772	34477	78253
R^2	0.038	0.038	0.041	0.034	0.033	0.126	0.133

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) adds country-times-year15 fixed effects. All interacted variables are demeaned such that the coefficient on female can be interpreted as the resulting gender numeracy gap. 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, OECD (2020), ILO (2022), SAO/NASA (2022).

5.5. *Decomposition of Numeracy Gaps*

In order to understand how the characteristics presented in Table 2 contribute to the formation of the gender gap in numeracy, we perform a decomposition of an estimated unconditional quantile regression, as suggested by Firpo et al. (2009). In particular, we first estimate the following unconditional quantile regression:

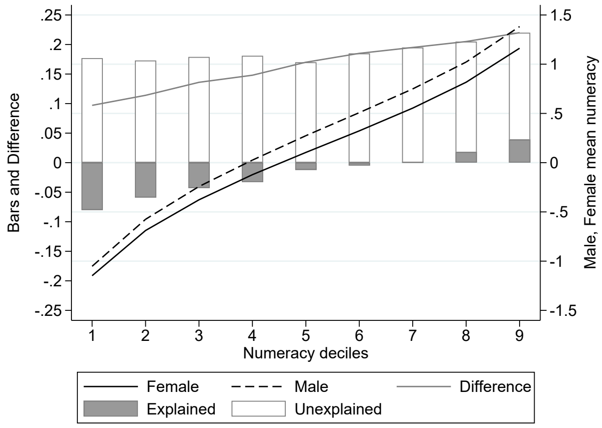
$$NS_{ic} = \alpha + \mathbb{X}_{ic}\mu + e_c + \epsilon_{ic}, \tag{2}$$

where NS_{ic} denotes the standardized numeracy score of an individual i from country c. $\mathbb{X}_{ic}$ comprises of the individual-level characteristics from Table 2: socio-demographics (four age groups and being a parent), educational groups (three categories: primary, secondary, tertiary), fields of study, and current occupation. e_c is a country dummy that we include in the Equation to control for differences in labor market institutions between countries. We estimate Equation (2) separately for men and women, and then perform the Kitagawa–Oaxaca–Blinder-style decomposition of 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).

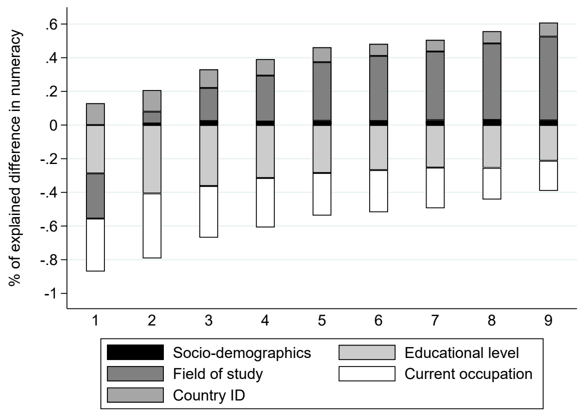
Figure 10 (A) presents the numeracy levels of men and women by numeracy decile (legend on the right axis), their difference, and its decomposition into the explained and unexplained parts (legend on the left axis). The figure documents that the numeracy gap grows slightly with increasing numeracy levels. The explained part actually contributes negatively to the differences in numeracy levels below the median, which implies that the observed characteristics should be associated with a smaller gender gap. Instead, at the top of the numeracy distribution, differences in observed characteristics explain a part of the gender numeracy gap. 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.11 contains a detailed decomposition of the explained

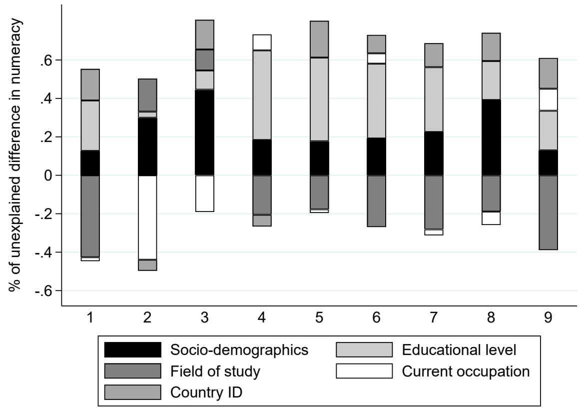
Figure 10: Decomposition of Numeracy Score Gaps, by Decile



(A) Explained vs. unexplained



(B) Explained



(C) Unexplained

Notes: Kitagawa–Oaxaca–Blinder type decomposition of gender numeracy gaps by numeracy decile for employed individuals aged 20 to 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.

part of the numeracy gap 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, differences in fields of study contribute 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.11 B). Overall, occupations explain a small proportion of the gap. 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.11 C). The country dummy that captures institutional differences, positively contributes to the gender gap in numeracy.

Figure 10 (C) presents the unexplained part of the gap associated with the same variable groups, whereas Figure B.12 provides details on the decomposition of the unexplained part by socio-demographics, field of study, and occupation. The largest contributors to the unexplained part of the gap (Figure 10C) are returns to socio-demographics and educational levels (that both explain part of the gap). Instead, observed returns to the field of study should be associated with a smaller gap than the one observed in the data. When looking at the detailed decomposition (Figure B.12), 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.

These results highlight the importance of parental status and field of study for the main patterns we find. Women's disadvantage at the top of the wage distribution is especially pronounced among parents and those with a non-STEM field of study whereas the patterns for childless individuals are much weaker and even partially reversed for STEM fields of study. Despite these striking patterns, parenthood and field of study as well as country- and cohort-specific institutional factors and many other characteristics usually associated with gender gaps in labor market outcomes cannot fully account for the gender gaps in numeracy skills among adults.

6. Conclusion

This paper presents new evidence on gender differences in numeracy skills and their relation to wage gaps. We use direct skill measures from the PIAAC dataset to study this relationship, hereby focusing on numeracy skills since they have shown to be particularly predictive of wages. Using PIAAC gives us the advantage of an objective skill measure for adults rather than relying on past educational levels that are often used in the literature.

We first study the relationship of numeracy levels with wages and document that, on average, higher skills translate into higher wages. This also applies when studying the longitudinal data from the short German PIAAC-L panel, where higher numeracy levels also correlate with higher wage growth. However, the described relationship of numeracy and wages is much weaker for women than for men. Looking at numeracy levels along the wage distribution reveals that men's numeracy levels exceed those of women at the bottom and especially at the top of the wage distribution. Using an unconditional quantile regression, we demonstrate that returns to numeracy are almost the same for women along the wage distribution, whereas they are increasing for men. We also observe these patterns 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 to and preserving higher numeracy levels in the long run.

Indeed, the numeracy differences of men of women are smaller for younger cohorts and larger 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 factors of particular importance. First, we document that having children is associated with 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. Second, we detect that being educated in STEM-related fields of study is related to higher numeracy levels of both men and women. However, we also document that the returns to numeracy are particularly high for STEM-educated women in the low-wage sector. When comparing education in STEM and being employed in a STEM industry, we 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. A decomposition of numeracy levels along its distribution confirms that the gender gap in numeracy largely depends on the field of study.

The evidence we present in this paper should be interpreted as descriptive in nature. 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 accompanying skill accumulation. Results suggest that numeracy skills used on the labor market are a possible important driver for wages that is not stable over time and can accumulate or depreciate depending on labor 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 preserving numeracy levels and measures against its depreciation are of particular importance to women, especially for mothers. Our findings also point at potential undesirable patterns for returns to skills: favoritism of numeracy skills for 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 preserving higher numeracy levels.

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A. Data Appendix

A.1. General Remarks

To make the procedures in this study comparable to related studies and to correct for possible data issues, we perform some standard procedures on the data. As suggested by Hanushek et al. (2015) and Hampf et al. (2020), we remove the Russian Federation since the Moscow region is entirely missing and hence the sample is not representative. Furthermore, we only use the first assessment for the United States from 2012. For Australia and Indonesia, no public use files are available on the PIAAC website (https://www.oecd.org/skills/piaac/about/).

A.2. Control Variables

The PIAAC survey offers a rich background questionnaire with many relevant information on individuals' personal lives and their labor market characteristics. The basic controls used in all presented regressions are a dummy for being female and age group dummies. The original gender variable provided in the PIAAC dataset is missing for one observation from the Netherlands (out of the original 223,139) which is dropped in our entire analysis. Furthermore, a continuous measure for age is available for 163,057/235,622 observations. The missing values come from Austria, Canada, Hungary, New Zealand, Singapore, and the US who only report age in five-year intervals from 16 to 65. In our study, we drop individuals aged 16-19 (18,221 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 to 29, 30 to 44, 45 to 54, and 55 to 65, the corresponding variable has no missing values.

Another important information presented in Table 2 states whether participants have children. The corresponding variable is taken as it is from the PIAAC dataset and has 2,564 missing values of which only a small part comes from individuals aged 16-19 (111 observations). The remaining missing values are within country and range from 0.01% in Canada to 8.84% in Belgium. The number of children is obtained from the top-coded version of a question on the number of children an individual has (top-coded at 4). This variable is missing for 82,948 respondents of which only 81 report to have children in the question explained above. Hence, the variable about having children is set to missing for these 81 individuals and set to zero for those 80,303 who report not to have children in the question above. Information about the number of children is hence missing for a total of 2,645 individuals.

An extended set of control variables includes information about individuals' education. The indicator for education levels is derived from a variable 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/reserach 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 2). This variable is missing for 2,455 observations; this number is composed of within-country missing values ranging from 0.00% (Finland) to 3.59% (Isreal).

A respondent's area of study in their highest qualification is reported in the categories presented in Table 2. In this original version, the variable is missing for 60,020/223,139 observations (of which 11,813 among the 16-19 year olds that are dropped as described above). The remaining 48,207 missing values are mainly individuals with lower secondary education or less (40,401 observations), so we decided to add it as a category for field of study in order to not lose them in the regressions. The remaining 7,806 missing values are within-country missing values (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 17 individuals aged 20 to 65) and their working hours. The categories used for the occupation refer to the 1-

digit ISCO standard and are presented in Table 2. The variable has 77,660 missing values of which 13,032 come from individuals aged 16-19. The remaining 64,628 missing values almost entirely come from individuals who report not to be employed at the moment (unemployed or out of the labor force), only 2,601 employed individuals are missing this variable. Again, this comes from within-country missing values 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 labor force as well as the reported working hours. The employment status of an individual is missing for 2,347 observations, most of which are aged above 19 and hence stay in our analysis (between 0.00% and 9.2% per country). Exploiting a question asking respondents to report their weekly working hours, we code a worker as employed full-time if the reported hours exceed 29 hours/week. The resulting variable is missing for 75,578 individuals of which 12,757 are 16-19 years old and will hence be excluded from our analysis. All non-missing values but one come from employed individuals and only 778 of the latter have missing information on their full-time status. Within-country missing values of working hours for employed individuals aged 20-65 range from 0.08% in Ireland to 2.35% in Israel.

A.3. 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 by country 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, 2016b). We standardize these measures to have mean 0 and standard deviation 1 within each country (using sampling weights). The exception to this are Figures 1, B.1, B.2, and B.3 where standardization is done across all countries using sampling weights in order to also show level differences in skills across countries. Throughout the analyses, we use the first plausible value of each skill measure (following Hanushek et al. (2015)).

A.4. Wages

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

Not all countries provide continuous information on their respondents' wages. As can be seen in Table B.1, four countries do not provide any wage information at all whereas another five countries only report the wage decile an individual is positioned in. For these five countries (Austria, Canada, Germany, Sweden, and the US), we are able to obtain country-specific information on each decile's median wage from Hanushek et al. (2015) 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 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 ranged from the temporal frames *per hour* to *per year*, but there was also an option for piece rates. Depending on the answer to this question, individuals were forwarded to the question asking them to report the gross salary in their preferred way. Furthermore, if individuals were unsure or unwilling to report their salaries precisely, they were forwarded to a question where they got presented wage categories on the basis of their respective national earnings distribution in which they could place themselves as an estimate of their own salary. Similarly, bonuses and other additional payments were assessed. For self-employed individuals, only monthly earnings were asked.[19]

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

[19] See OECD (2016a) and http://www.oecd.org/skills/piaac/bq_master.htm, last accessed November 03, 2022.

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 (2016a), chapter 20. The description here will focus on hourly earnings, details for monthly earnings can be found in OECD (2016a), 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, and gender, among others. The precise earnings of this "similar" respondent were then used to impute the respective earnings of the respondent who only reported wage intervals. This was done equivalently for bonuses/additional payments and monthly earnings. Furthermore, a variable indicating imputation of precise earnings was included (OECD, 2016a).

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 one 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.5. Sampling Weights

To give the same weight to each country in pooled regressions, we standardize the sampling weights. The original 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 and regarding relevant demographic characteristics. Since we do not wish to represent different sizes of countries in our pooled regressions and especially since the samples sizes are far from being proportional to relative populations, we adjust this variable to sum up to one in each country instead of its effective size. These adjusted weights are then used in our regressions throughout (if not specified otherwise).

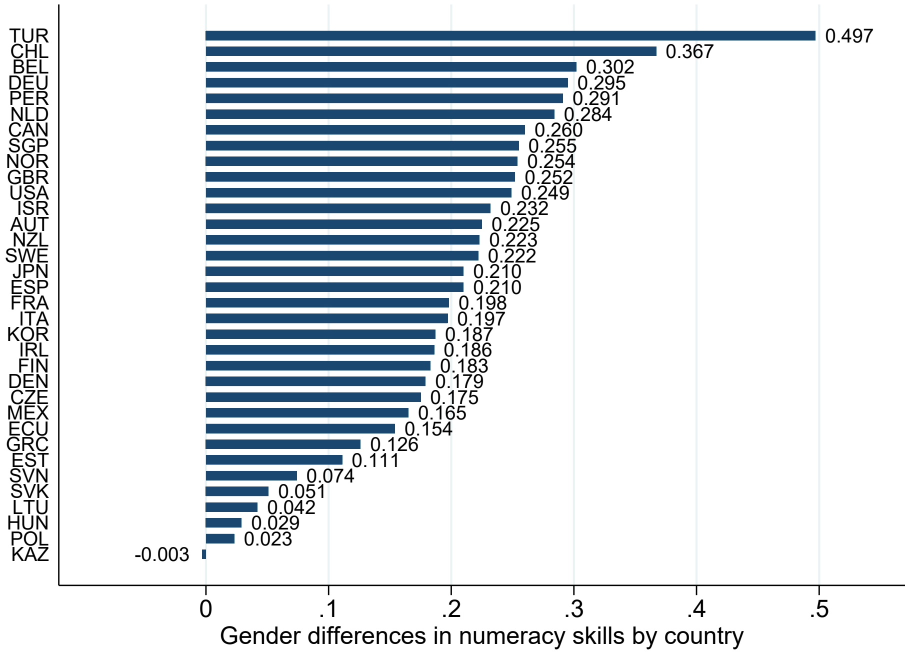
A.6. German Panel Dataset

As mentioned above, Germany assessed individual skills for the 2012 PIAAC sample again in 2015 to create a small panel dataset (GESIS – Leibniz Institute for the Social Sciences, German Socio-Economic Panel (SOEP) at DIW Berlin & LIfBi – Leibniz Institute for Educational Trajectories, 2017). Mostly, we apply the same corrections/transformations to the dataset as described in subsections A.3 and A.4. Hence, this subsection will focus on the differences only.

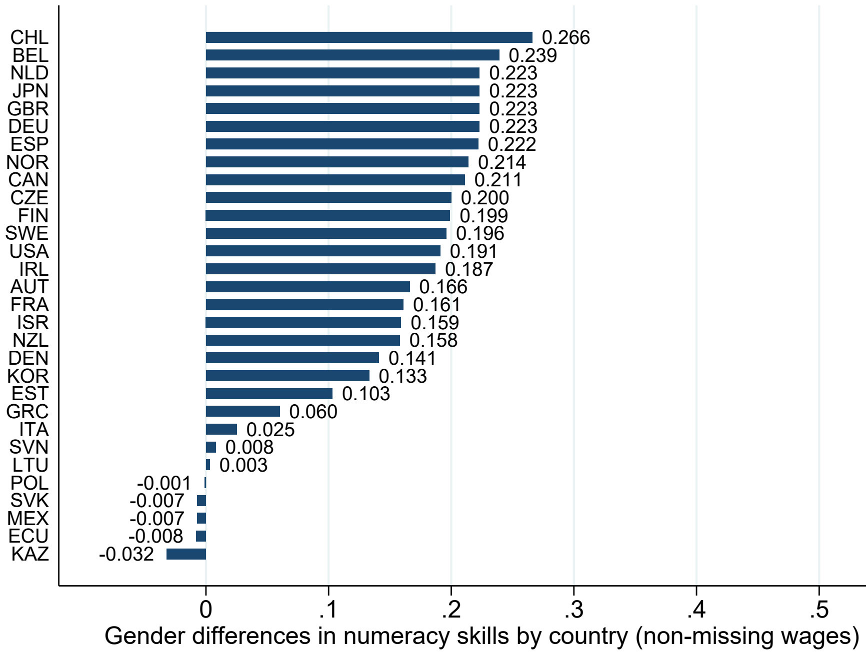
The re-sampling of German respondents took place from 2014 to 2016. In 2014, only household members aged 18 or above of the 2012 respondents were surveyed. In 2015, both the original 2012 respondents and their partners living in the household were surveyed in a similar way as in the original questionnaire in 2012, including a comparable skill assessment. The last sampling in 2016 again included household members aged 18 or above from the respective households. Since numeracy skills were only measured in a comparable way in 2015, we focus on the samples from 2012 and 2015 when using the German sample. Wages in 2015 are not available as 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 through a scientific use file from PIAAC-L such that we decided to use the best available measure in each year.

B. Appendix: Supplementary Figures and Tables

Figure B.1: Gender Gaps in Numeracy Scores



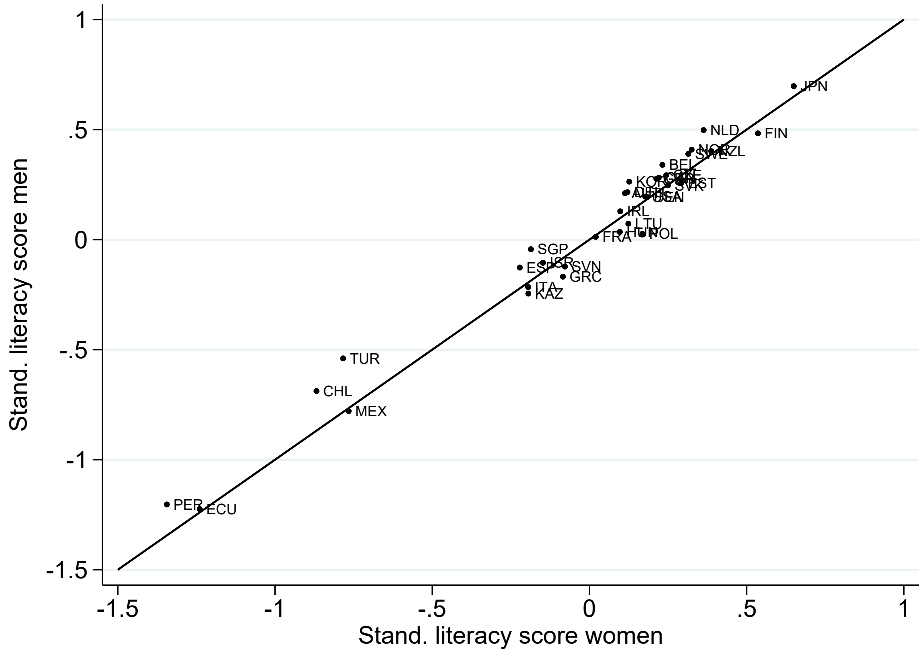
(a) All individuals



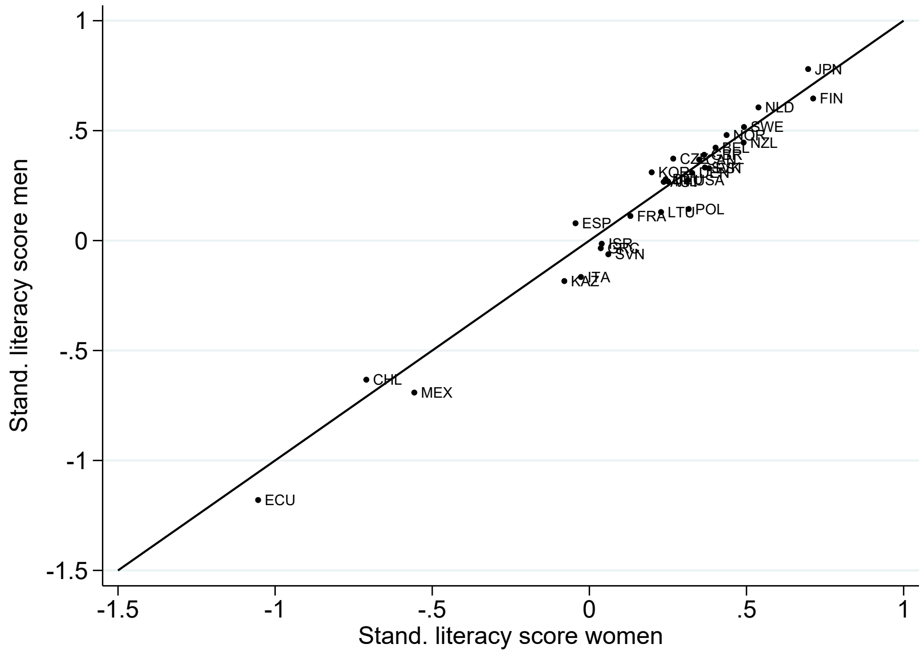
(b) Non-missing wages

Notes: Gender gaps in standardized numeracy scores for men and women aged 20 to 65 by country (all (a) or only those with non-missing wage (b)). Gender gaps represent coefficients for female of a regression of standardized numeracy scores on a female dummy, by country using sampling weights. Standardization across all countries uses individuals' sampling probability. Sample contains all individuals with non-missing numeracy scores (a; 202,633 individuals) and non-missing wages (b; 99,793 individuals). Data source: PIAAC international PUF 2012.

Figure B.2: Gender-Specific Literacy Scores



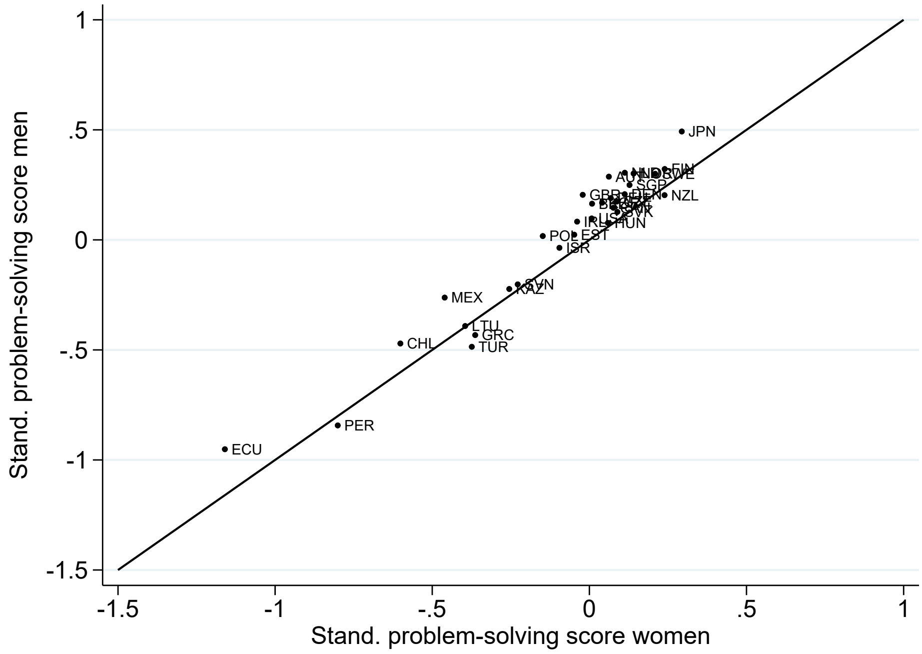
(a) All individuals



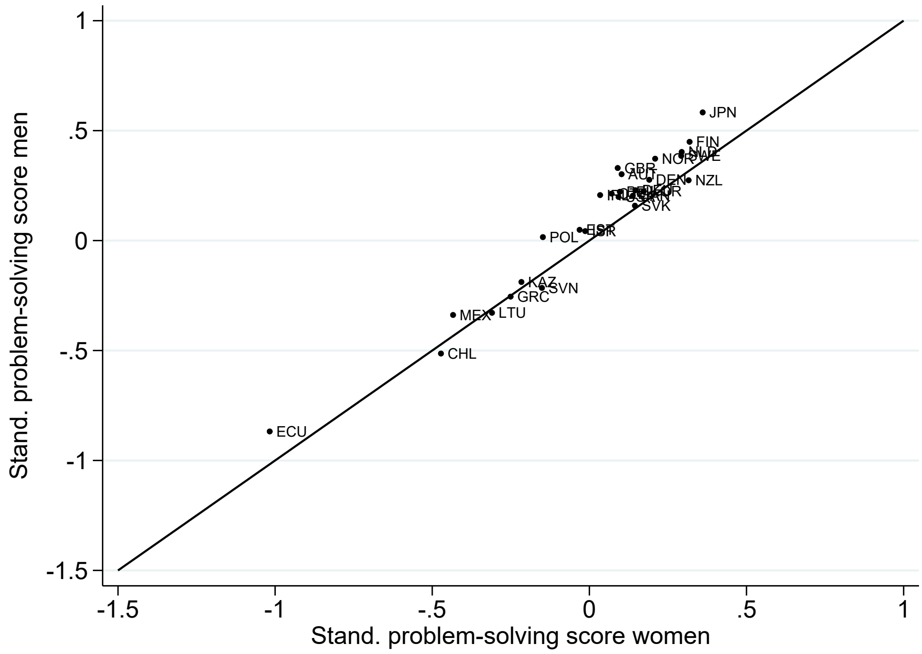
(b) Non-missing wages

Notes: Standardized literacy scores for men and women aged 20 to 65 by country. Standardization across countries 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 (a; 202,633 individuals) and non-missing wages (b; 99,793 individuals). Data source: PIAAC international PUF 2012.

Figure B.3: Gender-Specific Problem-Solving Scores



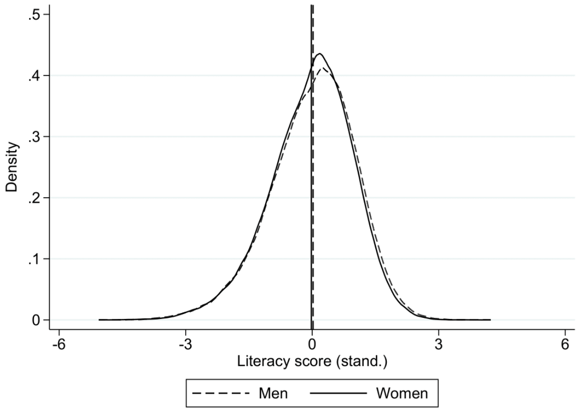
(a) All individuals



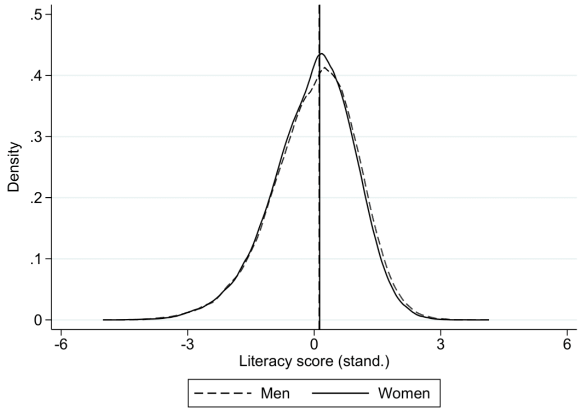
(b) Non-missing wages

Notes: Standardized scores for problem solving in technology-rich environments for men and women aged 20 to 65 by country. Standardization across countries 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 (a; 131,579 individuals) and non-missing wages (b; 73,802 individuals). Results look similar when just considering countries with earnings information (results available upon request). Data source: PIAAC international PUF 2012.

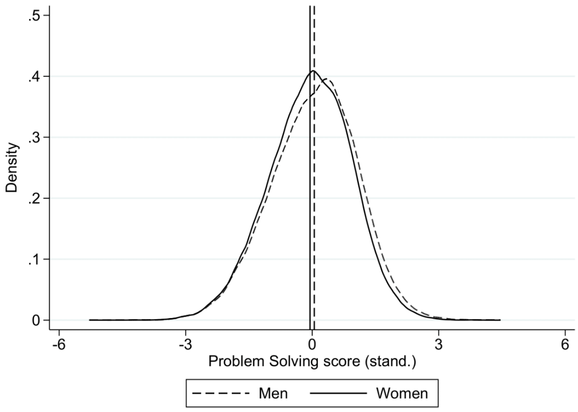
Figure B.4: Literacy and Problem-Solving by Gender



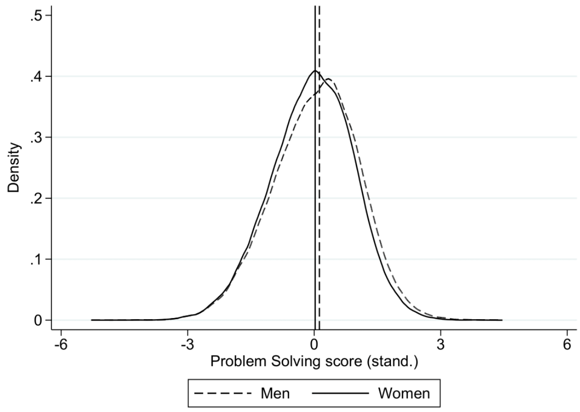
(a1) All individuals



(b1) Non-missing wages



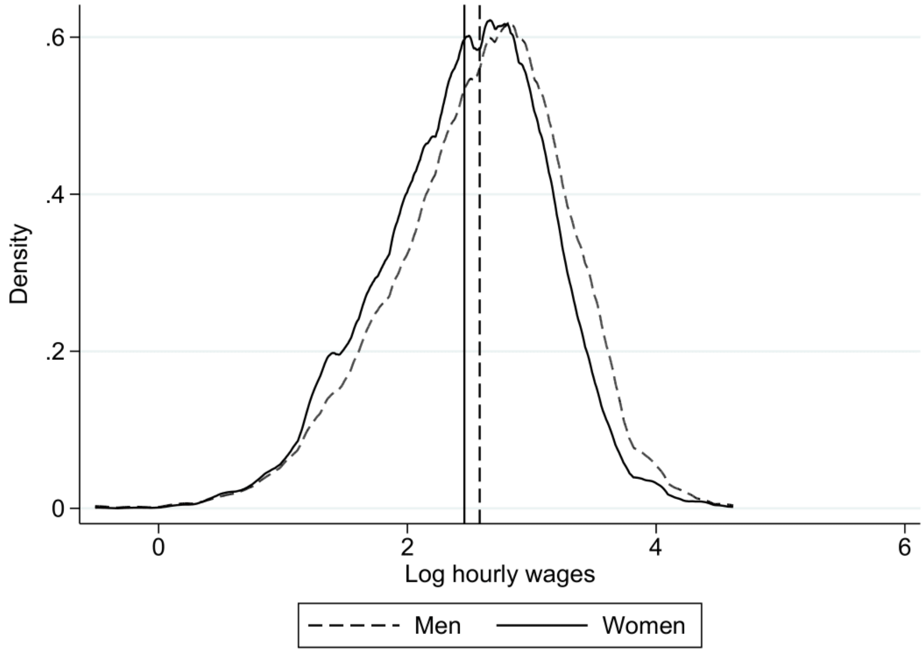
(a2) All individuals



(b2) Non-missing wages

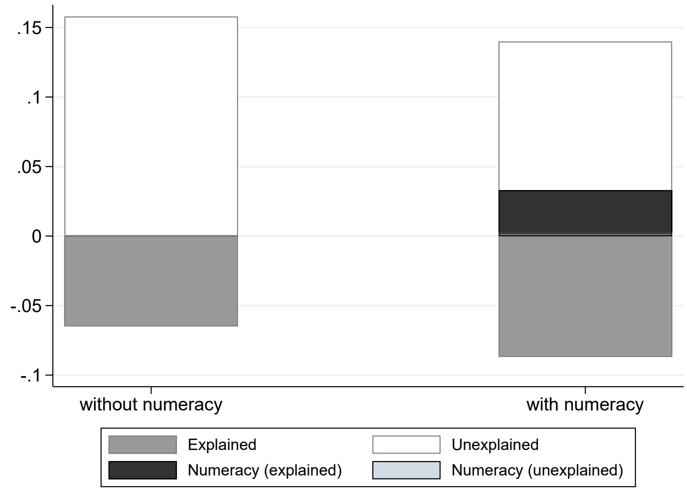
Notes: Standardized literacy and problem solving scores for men and women. Standardization by country uses individuals' sampling probability. Vertical lines represent the respective means for women and men. Sample contains all individuals with non-missing skill measures (a1: 202,633 individuals; a2: 131,579 individuals) and non-missing wages (b1: 99,793 individuals; b2: 73,802 individuals). Results look similar when just considering countries with earnings information (results available upon request). Data source: PIAAC international PUF 2012.

Figure B.5: Distribution of Gross Hourly Wages by Gender

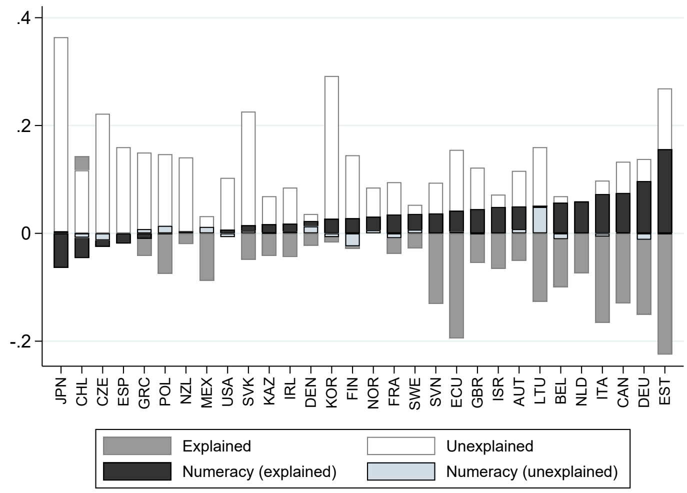


Notes: Log trimmed gross hourly wages (PPP-adjusted) for men and women. Wage measures are trimmed and imputed with decile medians if the continuous measure was not available. Vertical lines represent the respective means for women and men. Sample contains all individuals with wage information (99,799 individuals). Data source: PIAAC international PUF 2012.

Figure B.6: Skills and Gender Wage Gaps



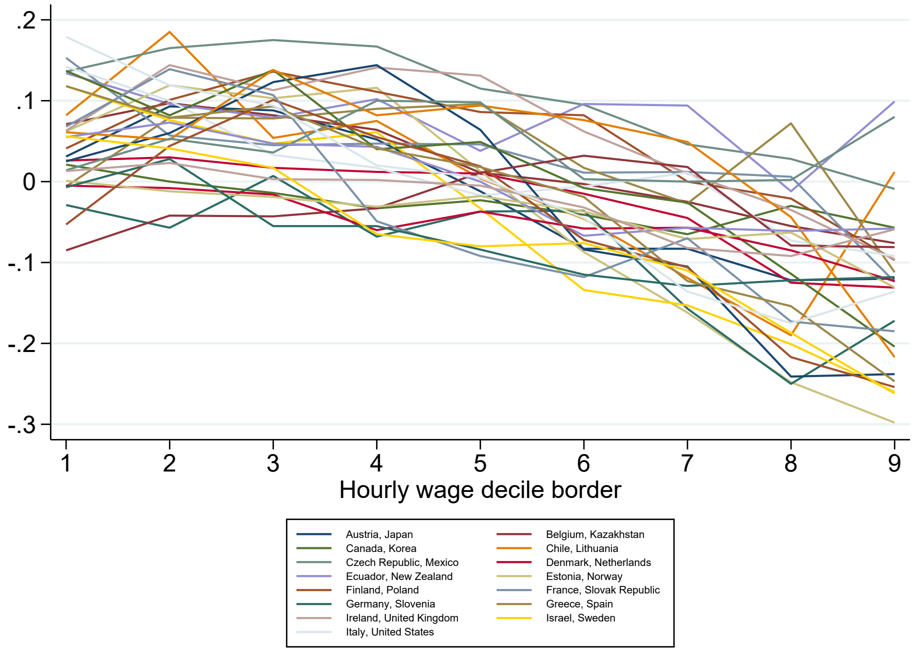
(A) On average



(B) By country

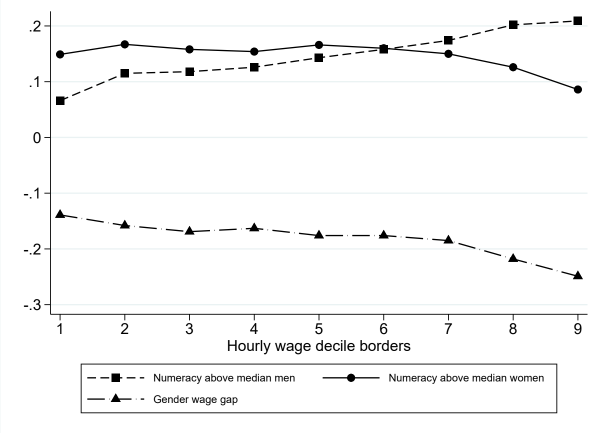
Notes: Kitagawa–Oaxaca–Blinder decomposition of gender gaps in hourly wages for employed individuals aged 20 to 65. Explanatory variables used: age groups, children, education, field of study, occupation, and country dummies. Numeracy scores are added as explanatory variables in second bar and in panel B. Sample contains all individuals with non-missing wages, numeracy scores, and all respective controls. Data source: PIAAC international PUF 2012.

Figure B.7: Returns to Numeracy, Women Relative to Men

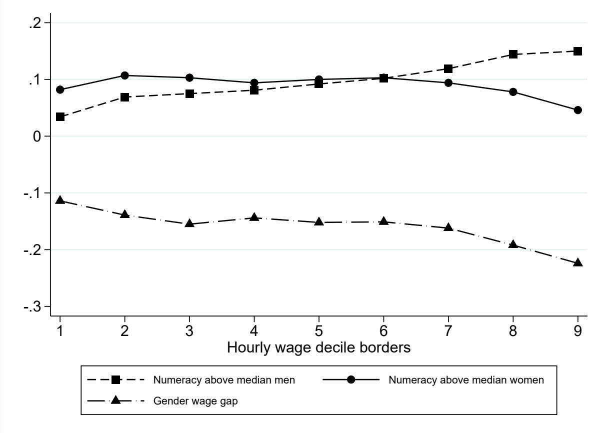


Notes: Plot of the coefficients presented in Equation 1 corresponding to unconditional quantile regressions with full controls (age groups, education levels, field of study, occupation, full-time status, children, and children*female, as in table B.6) at each wage decile border. Graphs represent returns to numeracy levels for women relative to men ($\widehat{\delta}$) as described above. Sample contains all individuals with non-missing wages and numeracy scores as well as the respective controls in each country (overall 96,174 individuals). Data source: PIAAC international PUF 2012.

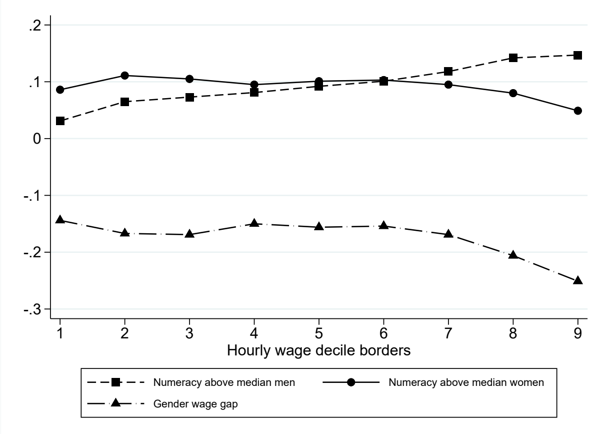
Figure B.8: Returns to Numeracy (with Additional Controls)



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



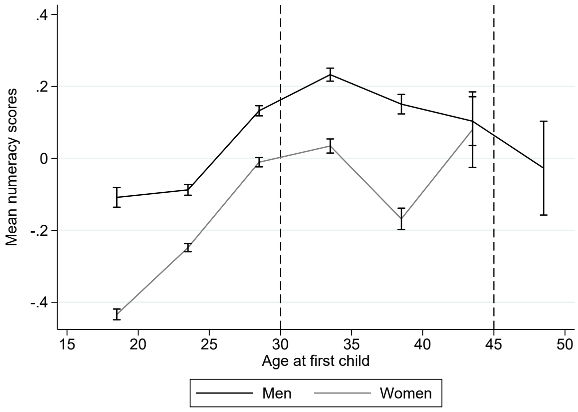
(B) Additional controls: occupation category



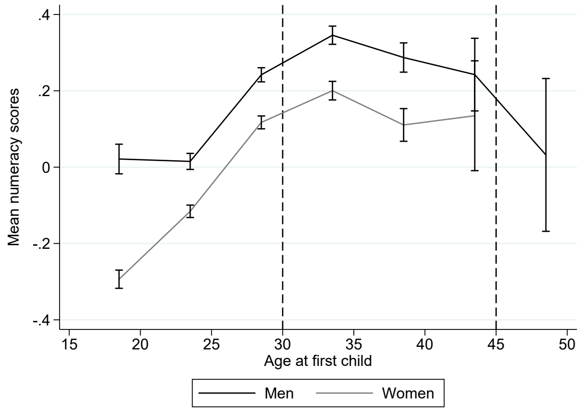
(C) Additional control: full-time indicator

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 2. 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 Table B.3, Table B.4, and Table B.5. Numeracy scores are standardized by country using individuals' sampling probability. Sample contains all individuals aged 20 to 65 with and non-missing wages, numeracy scores, and the respective controls (A: 97,080 individuals; B: 96,269 individuals; C: 96,234 individuals). Data source: PIAAC international PUF 2012.

Figure B.9: Numeracy by Gender and Age at First Childbirth

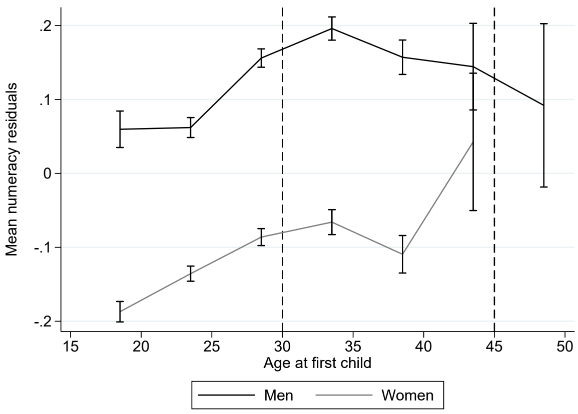


(a) All individuals

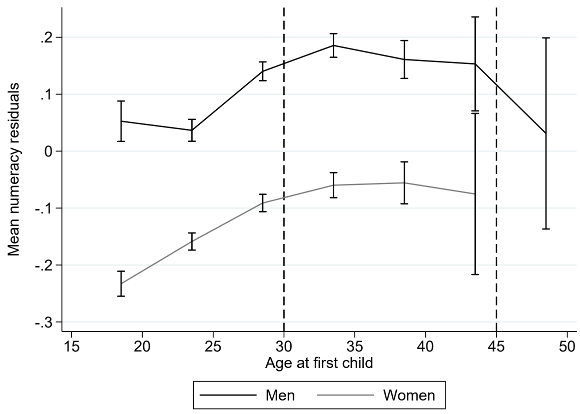


(b) Non-missing wages

(A) Unconditional



(a) All individuals

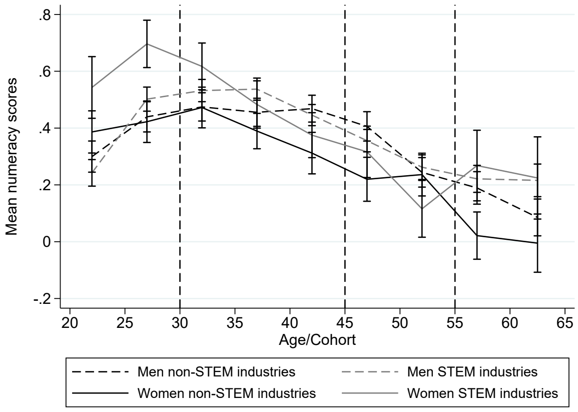


(b) Non-missing wages

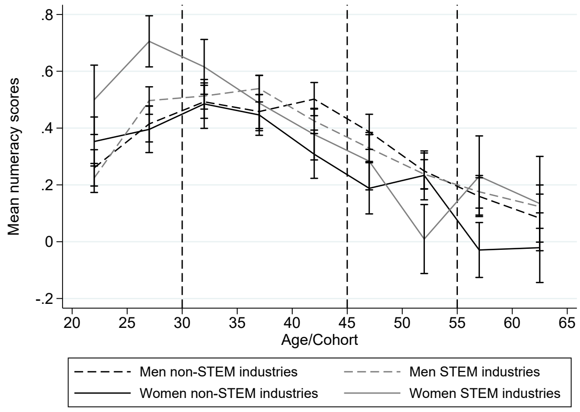
(B) Residual, after conditioning on educational levels

Notes: Mean standardized numeracy scores by age at birth of first child (in five-year intervals) for men and women aged 20 to 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 cut-offs of age groups used in the regressions at ages 30, 45, and 55. Standardization by country uses individuals' sampling probability. Sample contains all individuals with non-missing numeracy scores, age, and child information (unconditional A: 136,126 individuals; B: 65,730 individuals, residual A: 136,041 individuals; B: 65,689 individuals). Data source: PIAAC international PUF 2012.

Figure B.10: Numeracy across Cohorts, STEM vs non-STEM

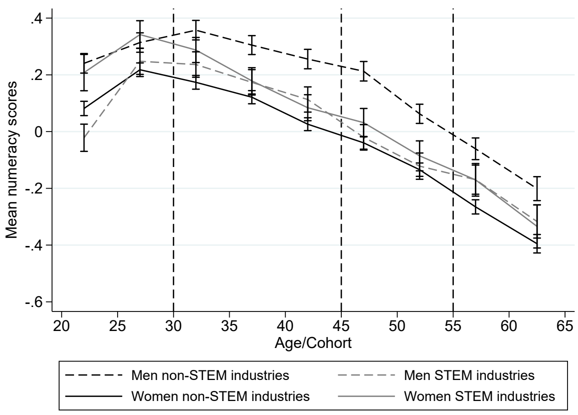


(a) All individuals

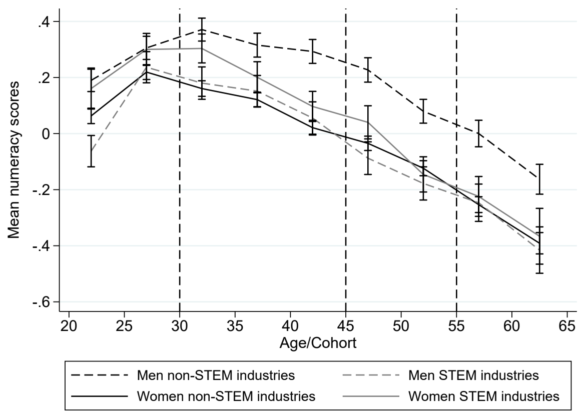


(b) Non-missing wages

(A) for respondents graduated in STEM field of study



(a) All individuals

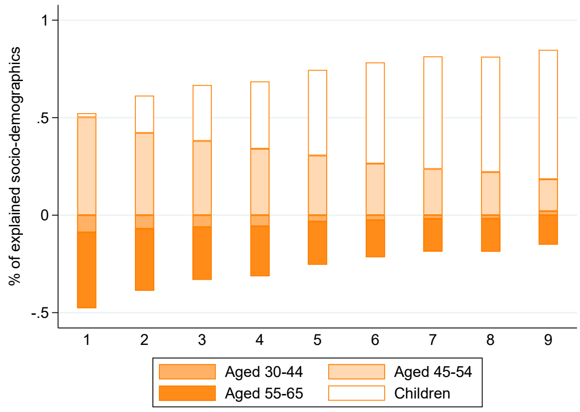


(b) Non-missing wages

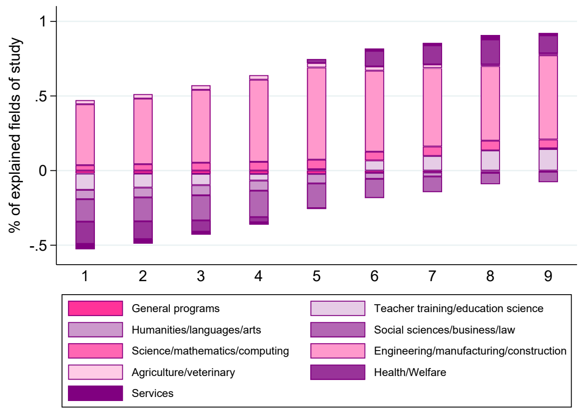
(B) for respondents graduated in non-STEM field of study

Notes: Mean standardized numeracy scores by age (in five-year intervals) for men and women with STEM (A)/non-STEM (B) fields of study in STEM v non-STEM industries. An industry is categorized as STEM if more than 50% of men working in this industry have their highest degree in a STEM field of study. Confidence intervals for each data point are added, vertical lines represent cut-offs of age groups in the regressions at age 30, 45, and 55. Standardization by country uses individuals' sampling probability. Sample contains all employed individuals with non-missing numeracy scores, age, and field of study (upper panel a: 33,636 individuals; b: 24,627 individuals; lower panel a: 97,001 individuals; b: 69,303 individuals). Data source: PIAAC international PUF 2012.

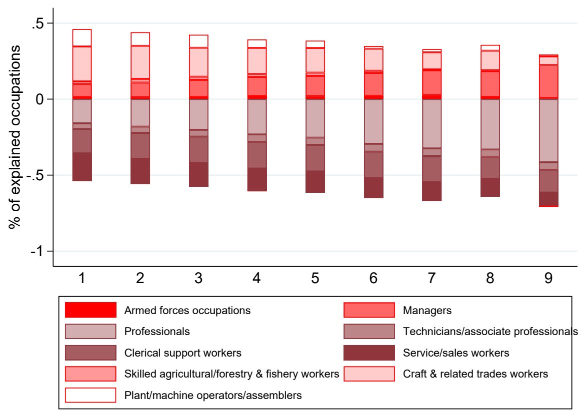
Figure B.11: Decomposition of the Gender Numeracy gap: Explained Part, Selected Groups



(A) Explained: Socio-demographics



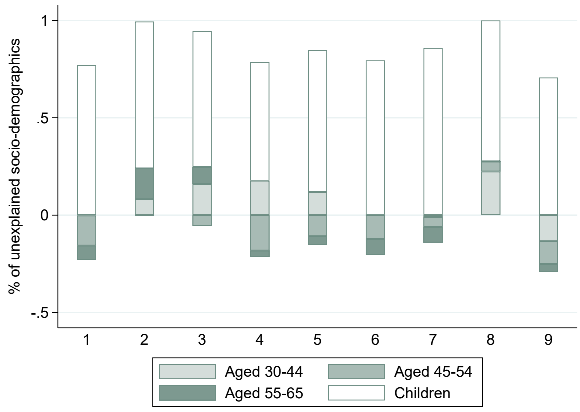
(B) Explained: Field of study



(C) Explained: Occupation

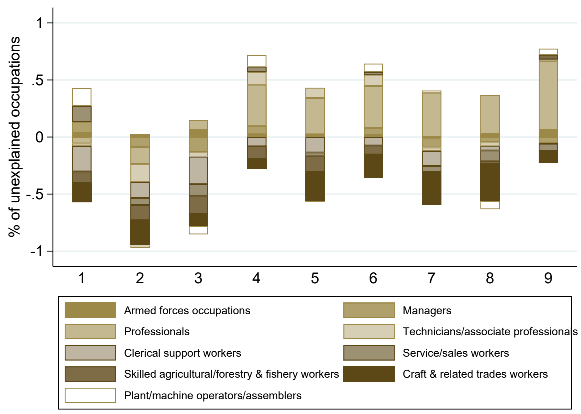
Notes: Explained part of a detailed Kitagawa–Oaxaca–Blinder type decomposition of gender numeracy gaps by numeracy decile using the command *oaxaca_rif*. Explanatory variables presented here: age groups and children (A), field of study (B), and occupation (C). Results look similar when just considering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

Figure B.12: Decomposition of 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 Kitagawa–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). Sample contains all individuals with non-missing numeracy, and 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
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
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	3,278
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			4,553	4,553	3,786	2,734 (D)
Total	34	21	8	5	202,633	202,633	131,579	99,799

Notes: The table contains the list of participating countries and their ISO codes (excluding Australia, Indonesia, Russia, and the US in 2017), 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. Note that the list does not include Russia, following the recommendation in the official PIAAC reports. For details also see Appendix A and https://www.oecd.org/skills/piaac/about/. Data source: PIAAC international PUF 2012.

Table B.2: Returns to Numeracy Levels (no Further Controls)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.166***	-0.161***	-0.167***	-0.145***	-0.148***	-0.136***	-0.118***	-0.099***	-0.092***
	(0.016)	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Aged 30-44	0.125***	0.183***	0.220***	0.259***	0.298***	0.304***	0.293***	0.276***	0.232***
	(0.014)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)
Aged 45-54	0.077***	0.152***	0.206***	0.271***	0.340***	0.369***	0.377***	0.371***	0.344***
	(0.016)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.010)
Aged 55-65	0.044*	0.142***	0.195***	0.257***	0.333***	0.373***	0.385***	0.391***	0.377***
	(0.018)	(0.013)	(0.012)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.013)
Numeracy above median	0.185***	0.233***	0.231***	0.233***	0.261***	0.279***	0.297***	0.334***	0.348***
	(0.014)	(0.011)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)
Numeracy above median * Female	0.077***	0.048**	0.038**	0.023*	0.012	-0.002	-0.031**	-0.081***	-0.132***
	(0.020)	(0.016)	(0.013)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99793	99793	99793	99793	99793	99793	99793	99793	99793

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 country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages and numeracy scores. Data source: PIAAC international PUF 2012.

Table B.3: Returns to Numeracy Levels (Further Controls I)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.222***	-0.210***	-0.209***	-0.191***	-0.199***	-0.178***	-0.161***	-0.142***	-0.126***
	(0.019)	(0.013)	(0.011)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Aged 30-44	0.093***	0.147***	0.184***	0.233***	0.273***	0.271***	0.264***	0.247***	0.201***
	(0.013)	(0.011)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)
Aged 45-54	0.069***	0.140***	0.191***	0.267***	0.342***	0.365***	0.377***	0.369***	0.341***
	(0.014)	(0.013)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)
Aged 55-65	0.036*	0.133***	0.183***	0.254***	0.334***	0.368***	0.386***	0.390***	0.378***
	(0.017)	(0.014)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.010)	(0.012)
Numeracy above median	0.066***	0.115***	0.118***	0.126***	0.143***	0.158***	0.174***	0.202***	0.209***
	(0.016)	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.010)
Numeracy above median * Female	0.083***	0.052**	0.040**	0.028*	0.023*	0.002	-0.024**	-0.076***	-0.124***
	(0.023)	(0.016)	(0.014)	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)	(0.012)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97080	97080	97080	97080	97080	97080	97080	97080	97080

Notes: Corresponding table for Figure B.8 (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, and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages, numeracy scores, and respective controls. Data source: PIAAC international PUF 2012.

Table B.4: Returns to Numeracy Levels (Further Controls II)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.161***	-0.178***	-0.183***	-0.156***	-0.160***	-0.152***	-0.138***	-0.126***	-0.120***
	(0.018)	(0.014)	(0.011)	(0.010)	(0.009)	(0.008)	(0.007)	(0.008)	(0.010)
Aged 30-44	0.065***	0.120***	0.156***	0.200***	0.235***	0.239***	0.231***	0.214***	0.165***
	(0.015)	(0.011)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Aged 45-54	0.037*	0.109***	0.158***	0.226***	0.293***	0.323***	0.334***	0.326***	0.296***
	(0.016)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Aged 55-65	0.003	0.101***	0.146***	0.210***	0.282***	0.322***	0.340***	0.342***	0.327***
	(0.019)	(0.012)	(0.012)	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)	(0.013)
Numeracy above median	0.034*	0.069***	0.075***	0.081***	0.092***	0.102***	0.119***	0.144***	0.150***
	(0.014)	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.010)
Numeracy above median * Female	0.048*	0.039**	0.028*	0.012	0.008	0.001	-0.025*	-0.066***	-0.104***
	(0.020)	(0.015)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96269	96269	96269	96269	96269	96269	96269	96269	96269

Notes: Corresponding table for Figure B.8 (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, and country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages, numeracy scores, and respective controls. Data source: PIAAC international PUF 2012.

Table B.5: Returns to Numeracy Levels (Further Controls III)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.199***	-0.212***	-0.202***	-0.164***	-0.166***	-0.156***	-0.146***	-0.144***	-0.153***
	(0.019)	(0.014)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.010)
Aged 30-44	0.079***	0.133***	0.164***	0.203***	0.237***	0.240***	0.234***	0.220***	0.177***
	(0.015)	(0.011)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Aged 45-54	0.051**	0.121***	0.165***	0.229***	0.295***	0.324***	0.337***	0.332***	0.308***
	(0.017)	(0.013)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)
Aged 55-65	0.004	0.101***	0.146***	0.210***	0.283***	0.322***	0.340***	0.342***	0.327***
	(0.018)	(0.014)	(0.011)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.012)
Numeracy above median	0.031*	0.065***	0.073***	0.081***	0.092***	0.101***	0.118***	0.142***	0.147***
	(0.015)	(0.012)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.010)
Numeracy above median * Female	0.056**	0.046**	0.032**	0.014	0.010	0.002	-0.023*	-0.062***	-0.098***
	(0.020)	(0.014)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(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	96234	96234	96234	96234	96234	96234	96234	96234	96234

Notes: Corresponding table for Figure B.8 (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, numeracy scores, and respective controls. Data source: PIAAC international PUF 2012.

Table B.6: Returns to Numeracy Levels (Further Controls IV)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.136***	-0.142***	-0.151***	-0.118***	-0.119***	-0.117***	-0.096***	-0.067***	-0.053***
	(0.024)	(0.019)	(0.014)	(0.013)	(0.011)	(0.011)	(0.010)	(0.012)	(0.014)
Aged 30-44	0.079***	0.117***	0.149***	0.188***	0.214***	0.213***	0.204***	0.191***	0.144***
	(0.016)	(0.012)	(0.010)	(0.008)	(0.009)	(0.008)	(0.007)	(0.008)	(0.009)
Aged 45-54	0.049**	0.100***	0.146***	0.209***	0.266***	0.289***	0.299***	0.294***	0.265***
	(0.019)	(0.014)	(0.011)	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)
Aged 55-65	0.002	0.079***	0.125***	0.188***	0.251***	0.285***	0.298***	0.300***	0.279***
	(0.022)	(0.016)	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)	(0.011)	(0.014)
Numeracy above median	0.031*	0.067***	0.074***	0.082***	0.093***	0.102***	0.119***	0.144***	0.149***
	(0.014)	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Numeracy above median * Female	0.051*	0.042*	0.029*	0.011	0.007	0.000	-0.025**	-0.067***	-0.104***
	(0.020)	(0.017)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)
child	0.044**	0.080***	0.066***	0.064***	0.080***	0.083***	0.097***	0.115***	0.140***
	(0.015)	(0.012)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.012)
Children × Female	-0.091***	-0.104***	-0.076***	-0.069***	-0.073***	-0.061***	-0.078***	-0.116***	-0.151***
	(0.022)	(0.016)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.015)
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	96174	96174	96174	96174	96174	96174	96174	96174	96174

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, numeracy scores, and respective controls. Data source: PIAAC international PUF 2012.

Table B.7: Returns to Numeracy Levels for those Without Children (no Further Controls)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.061*	-0.042*	-0.063***	-0.045***	-0.063***	-0.061***	-0.054***	-0.035*	-0.019
	(0.026)	(0.019)	(0.016)	(0.013)	(0.014)	(0.012)	(0.014)	(0.014)	(0.016)
Aged 30-44	0.131***	0.177***	0.220***	0.230***	0.281***	0.284***	0.308***	0.322***	0.280***
	(0.016)	(0.014)	(0.012)	(0.009)	(0.011)	(0.010)	(0.011)	(0.012)	(0.016)
Aged 45-54	0.074***	0.107***	0.178***	0.220***	0.314***	0.358***	0.386***	0.450***	0.481***
	(0.022)	(0.018)	(0.016)	(0.014)	(0.014)	(0.014)	(0.016)	(0.020)	(0.027)
Aged 55-65	0.020	0.118***	0.188***	0.227***	0.295***	0.349***	0.390***	0.445***	0.521***
	(0.030)	(0.022)	(0.021)	(0.016)	(0.019)	(0.020)	(0.021)	(0.025)	(0.038)
Numeracy above median	0.158***	0.231***	0.203***	0.203***	0.221***	0.218***	0.232***	0.263***	0.260***
	(0.020)	(0.018)	(0.014)	(0.012)	(0.012)	(0.013)	(0.012)	(0.014)	(0.019)
Numeracy above median * Female	0.045	-0.002	0.013	-0.003	0.009	0.006	-0.003	-0.031	-0.053*
	(0.030)	(0.025)	(0.019)	(0.017)	(0.018)	(0.016)	(0.017)	(0.019)	(0.023)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32371	32371	32371	32371	32371	32371	32371	32371	32371

Notes: Corresponding table for Figure 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 country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals without children and with non-missing data for wages and numeracy scores. Data source: PIAAC international PUF 2012.

Table B.8: Returns to Numeracy Levels for those With Children (no Further Controls)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.204***	-0.214***	-0.220***	-0.215***	-0.195***	-0.161***	-0.133***	-0.115***	-0.097***
	(0.018)	(0.014)	(0.012)	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Aged 30-44	0.146***	0.166***	0.159***	0.213***	0.229***	0.227***	0.215***	0.199***	0.174***
	(0.030)	(0.021)	(0.018)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)
Aged 45-54	0.096**	0.138***	0.144***	0.228***	0.270***	0.290***	0.292***	0.278***	0.251***
	(0.032)	(0.022)	(0.019)	(0.016)	(0.015)	(0.012)	(0.011)	(0.012)	(0.012)
Aged 55-65	0.077*	0.127***	0.133***	0.211***	0.266***	0.291***	0.294***	0.293***	0.293***
	(0.032)	(0.022)	(0.020)	(0.017)	(0.015)	(0.014)	(0.012)	(0.013)	(0.013)
Numeracy above median	0.198***	0.235***	0.251***	0.264***	0.297***	0.323***	0.347***	0.378***	0.373***
	(0.019)	(0.014)	(0.012)	(0.011)	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)
Numeracy above median * Female	0.072**	0.064***	0.039**	0.030*	0.004	-0.036**	-0.072***	-0.131***	-0.181***
	(0.024)	(0.018)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.015)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67351	67351	67351	67351	67351	67351	67351	67351	67351

Notes: Corresponding table for Figure 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 country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with children and non-missing data for wages, numeracy scores. Data source: PIAAC international PUF 2012.

Table B.9: Returns to Numeracy Levels, non-STEM Field of Study (no Further Controls)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.112***	-0.100***	-0.129***	-0.106***	-0.117***	-0.095***	-0.091***	-0.077***	-0.087***
	(0.020)	(0.014)	(0.011)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)
Aged 30-44	0.117***	0.156***	0.194***	0.247***	0.297***	0.298***	0.287***	0.272***	0.230***
	(0.019)	(0.013)	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)
Aged 45-54	0.056**	0.134***	0.184***	0.255***	0.328***	0.360***	0.374***	0.363***	0.349***
	(0.021)	(0.015)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Aged 55-65	0.041	0.126***	0.176***	0.249***	0.331***	0.373***	0.391***	0.388***	0.389***
	(0.021)	(0.016)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.014)
Numeracy above median	0.182***	0.231***	0.215***	0.235***	0.256***	0.283***	0.299***	0.333***	0.367***
	(0.019)	(0.015)	(0.012)	(0.010)	(0.012)	(0.011)	(0.010)	(0.011)	(0.015)
Numeracy above median * Female	0.042	0.027	0.027	0.005	0.011	-0.011	-0.031*	-0.083***	-0.144***
	(0.026)	(0.018)	(0.014)	(0.012)	(0.013)	(0.011)	(0.012)	(0.014)	(0.017)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71836	71836	71836	71836	71836	71836	71836	71836	71836

Notes: Corresponding table for Figure 8 (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 country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages, numeracy scores, and their field of study classified as non-STEM. Data source: PIAAC international PUF 2012.

Table B.10: Returns to Numeracy Levels, STEM Field of Study (no Further Controls)

	Outcome: Log Hourly Wages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.389***	-0.361***	-0.234***	-0.220***	-0.199***	-0.140***	-0.109***	-0.081***	-0.056***
	(0.055)	(0.036)	(0.025)	(0.023)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Aged 30-44	0.143***	0.191***	0.227***	0.280***	0.284***	0.288***	0.293***	0.279***	0.220***
	(0.024)	(0.023)	(0.019)	(0.016)	(0.014)	(0.014)	(0.012)	(0.014)	(0.013)
Aged 45-54	0.091***	0.139***	0.223***	0.323***	0.354***	0.372***	0.376***	0.380***	0.342***
	(0.026)	(0.025)	(0.022)	(0.017)	(0.015)	(0.015)	(0.013)	(0.017)	(0.016)
Aged 55-65	0.038	0.137***	0.180***	0.277***	0.305***	0.336***	0.370***	0.377***	0.371***
	(0.031)	(0.027)	(0.024)	(0.020)	(0.018)	(0.019)	(0.017)	(0.019)	(0.022)
Numeracy above median	0.187***	0.226***	0.229***	0.231***	0.223***	0.249***	0.285***	0.304***	0.265***
	(0.023)	(0.019)	(0.017)	(0.014)	(0.012)	(0.012)	(0.012)	(0.014)	(0.017)
Numeracy above median * Female	0.260***	0.200***	0.093**	0.071*	0.055*	-0.010	-0.045*	-0.069**	-0.089***
	(0.058)	(0.040)	(0.030)	(0.029)	(0.023)	(0.020)	(0.022)	(0.023)	(0.023)
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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25258	25258	25258	25258	25258	25258	25258	25258	25258

Notes: Corresponding table for Figure 8 (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 country fixed effects at each wage decile, weighted by individual sampling probability. Estimation sample contains all individuals with non-missing data for wages, numeracy scores, and their field of study classified as STEM. Data source: PIAAC international PUF 2012.