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Gender gaps in skills and labor market outcomes: evidence from the PIAAC

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Abstract
Our paper makes the first attempt to address the empirical relationRicship between cognitive skills and gender gaps in labor market performance. We do so in a cross-country setting. To that end we use the PIAAC dataset, which contains information on OECD and non-OECD economies. Firstly, we document the existence of gender gaps in cognitive skills for numeracy, which are found to be around 2.5–4.6% and increase with age. These gaps remain even when comparing men and women within the same level and field of study. Next, we document sizable gender gaps in labor market outcomes, such as Labor Force Participation and hourly wages—around 18%, increase with age and rise remarkably for parents. Math skills are positively and strongly associated with these two labor market outcomes and its contribution to explain gender gaps, although significant, is limited—between 10 15% at most—in particular for parents.

JEL classification J16 · J24 · J31

Keywords Gender wage gap · Gender gap in labor force · Cognitive skills · PIAAC

1 Introduction

Over the last twenty years, there has been a narrowing of gender gaps in different labor market outcomes such as employment rates, hours worked, and wage rates, among others, in all advanced economies, mainly driven by a large expansion in women's education. However, these gender gaps still continue even after proxies for human capital endowments of workers—such as education, age or experience—are

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taken into account (Blau et al. 2008; England et al. 2012; Blau and Kahn 2017). This is referred to as the “unexplained” or “adjusted” gender gap and, as some empirical papers show (see Blau and Kahn 2017; Boll et al. 2016), unexplained factors still accounted for a substantial share of the observed wage gender gap.[1]

In this paper we propose to test whether the use of more direct measures of human capital endowment help understanding this unexplained component of the gender gap in labor market outcomes. To this end, we take advantage of the appearance of new datasets that offer direct measures of cognitive competences. In particular, the Programme for the International Assessment of Adult Competences (PIAAC) offers individual measures of cognitive skills for the adult population across a significant number of countries. Our paper deals precisely with the association between the adjusted gender gaps in labor market outcomes and gender gaps in cognitive skills. To measure such association, we believe that cross-country variation provides clearer evidence than within-country analysis because of the better picture of broad differences in the social and economic environment.

Our precise contribution with respect to previous studies is threefold: first, this paper uses precise measures of cognitive skills provided by PIAAC to assess whether gender gaps exist in cognitive skills for different ages, educational levels, fields of specialization, occupation and across countries and assess their magnitude. Second, we focus on the relationship between gender gaps in math skills and labor force participation, which to our knowledge, has not previously been addressed. Precisely, we seek to explore the link between math skills and self-selection into the labor market, particularly for women. Third, we investigate the link between gender gaps in math skills and gender gaps in wages. If there is a link between cognitive skills and labor market outcomes, gender inequalities in the acquisition of these skills emerge as an important policy issue, both from equity and efficiency grounds. We are particularly interested in comparing findings at entry age (24–29) and at the next age group (30–39), where motherhood mostly takes place. Cognitive skills at ages 24–29 are mainly determined by the acquisition of these skills during the process of formal education whereas for the other age-groups, current cognitive levels might depend on educational attainment levels as well as on particular labor market paths. This perspective provides a more holistic view of how the link between gender gaps in cognitive skills and labor market outcomes evolve through life. Gender gaps in areas such as wages and hours worked change substantially at different stages of the life cycle as a result of motherhood. Moreover, educational attainment may still play a role in explaining gender differences for older workers but not so much for younger workers.

In related literature, cognitive skills have been found to be positively associated with the success of individuals in the labor market, participation in society, and economic growth (Hanushek and Woessmann 2015; Oreopoulos and Salvanes 2011; Quintini 2014; Hanushek and Woessmann 2015; Hanushek et al. 2015; Hampf et al. 2017). For instance, Hanushek et al. (2015) find that one-standard-deviation increase in numeracy skills is associated with an 18% wage increase among prime age workers. However, there is hardly any evidence on the association between properly

[1] Blau and Kahn (2017) estimate this unexplained component is around 85% of the raw gender gap. Boll et al. (2016) estimate this is around 60%.

measured skills in the labor market and gender gaps observed in different labor market outcomes. So far, only Hanuseck et al. (2015) and Fortin (2008) provide some insights on the link between cognitive abilities and gender wage gaps, although their empirical analysis does not seek to measure the role of gender gaps in cognitive skills with a view to explaining gender gaps in labor market performance.

The assessment of gender differences in cognitive skills, particularly in numeracy skills in adulthood, is appealing since results from PISA persistently find that females at age 15 perform consistently around 5% more poorly in numeracy skills than their male counterparts (see Arora and Pawlowski 2017). Such gender disparities may lead, at least partly, to the documented lower presence of women in the fields of study of science, technology, engineering, and mathematics. Joensen and Nielsen (2014) shows that encouraging more students to opt for advanced mathematics has a sizeable positive earnings effects for girls, but no effect for boys at the margin. Early mathematical knowledge predicts later success in school, and even in high school, and it correlates with a variety of higher cognitive skills (Clements and Sarama 2011). Moreover, the gender segregation by occupation observed in the labor market —young women tend to study fields such as education, health, and social sciences whereas technical studies are primarily male fields—may also be a consequence of the poorer performance of girls in numeracy skills. Hence, it is necessary to document empirically the size of gender gaps in cognitive skills, particularly in numeracy skills, and then assess the extent to which such gender disparities are associated with labor market performance in order to deep into the drivers of gender gaps in the labor market.

Gender gaps in labor market outcomes are likely to be heterogeneous depending on family composition, basically, whether or not there are children in the household. In most developed countries, women must combine employment with home responsibilities to a greater extent than their male partners. This affects their decisions with respect to their labor supply (i.e., time employed, type of job and so on) and hence their human capital accumulation in general and in particular the accumulation of skills along the life cycle.[2] To account for this, in our empirical analysis we test whether the association of gender gaps in cognitive skills and labor market outcomes differs for parents and non-parents.

Data shows that on average gender gaps in literacy skills are negligible even on entry into the labor market and remain so at different ages. However, in numeracy skills, men score around 4.2% higher than females (a difference of around 11–12 points on a 500-point scale). This gap increases from 3.6% at the age of entry into the labor market (24–29 age group) to 4.6% for the 40–49 age group. Additionally, we show that gaps in numeracy skills are heterogeneous by level and field of study and by occupational groups. Concerning labor market outcomes, we find sizable gender gaps in labor force participation and wages (around 18 percentage points and 20%, respectively), even when comparing men and women with similar general human capital endowments (i.e., age, educational level and field of study). Moreover, gender

[2] For instance, previous studies have concluded that for women, being married and having young children reduce labor force participation and the probability of paid employment, whereas for men being married increases labor force participation and the probability of paid work and having young children has no significant impact.

differences in math skills are associated with gender gaps in labor force participation, particularly for workers less than 40 years old and for non-parents. For instance, adjusted gender gap in labor participation drops from 17.7 percentage points to 16.8 percentage points (a drop of one percentage point or 5.1% in relative terms) when maths skills are factored in the model, even when comparing individuals with the same level and field of studies. Lastly, turning to gender wage gaps, they rise substantially and steadily with age—from 9% at age entry, rise to 19% at the "maternity age" and rise again to 23% for 40–49 years. For parents, adjusted gender wage gaps are around twice as large as those for non-parents (12% for non-parents versus 24% for parents). The contribution of gender gaps in math skills to explain gender wage gaps vary between 1.0–2.9 percentage points or between 11–15% in relative terms. Nevertheless, adjusted gender gaps in wages and in labor market participation are still significant even when factoring in math skills in the corresponding equation. This indicates that there are still unobserved factors which underly gender gaps in labor market outcomes other than difference in math cognitive skills.

The rest of the paper is organized as follows: Section 2 describes the main characteristics of the dataset used. Section 3 presents firstly main sample statistics for gender gaps in literacy and numeracy skills by different individual characteristics. Secondly, Section 3 also display adjusted gender gaps in literacy and numeracy skills. Section 4 focuses on the relationship between math skills and gender gaps in labor market outcomes. This Section 4, firstly present main sample statistics for gender gaps in labor market outcomes and secondly adjusted gender gaps for these labor market outcomes with and without math skills, once main sample covariates are considered. Section 5 concludes.

2 The Programme for the International Assessment of Adult Competencies (PIAAC)

The data source used in the paper is the Programme for the International Assessment of Adult Competencies (PIAAC), developed by the OECD to provide internationally comparable data on the skill levels of the adult population. The first round of PIAAC data, collected between August 2011 and March 2012, produced data on mostly OECD countries (see OECD 2013). In a second round,[3] PIAAC conducted the same skill survey in nine more countries (including both non-OECD countries and new members of the OECD) between April 2014 and March 2015 extending the usable sample with comparable skill data to 23 countries with information on wages (though the total number of countries is 31). In each participating country a representative sample of adults between 16 and 65 years of age was interviewed at home in the language of their country of residence.[4]

[3] Round-1 countries: Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Slovak Republic, Spain, United Kingdom. Round-2 countries: Chile, Greece, Israel, Lithuania, New Zealand, Slovenia.

[4] At least 5000 adults participated in the PIAAC assessment in each country.

The PIAAC was designed to measure key cognitive skills needed for individuals to advance at work and participate in society. This database allows to distinguish workers by a broader sets of abilities, generally accumulated over one's lifetime, that shape their decisions and success in the labor market. In that sense, these direct measures of cognitive skills may provide more adequate estimations of the differences in individuals' potential productive capacity than is provided by the quantity of education they receive. PIAAC is also valuable since it extends the information obtained from the various PISA waves, which measured those skills at the age of 15 at the same time that links these new skill variables with socioeconomic and labor market covariates. The combination of these two sets of information gives greater value to this database. In particular, the survey includes three main sets of information: First, a personal interview comprising a questionnaire about personal background, educational attainment and training, current work status, wages, and work history. Information on family background, linguistic background, health status, and civic participation is also provided. Second, there is an assessment of cognitive skills in three domains—literacy[5] (mainly Literacy skills), numeracy, and problem-solving skills in technological settings. The assessments are explicitly implemented as international or cross-national assessments designed to provide valid, reliable measures of proficiency across different countries, languages, and cultures. This unique information on skills at individual level, together with standard labor market information such as wages, educational attainment, labor market experience, and type of job makes the PIAAC a highly suitable data source for our purpose. Gender gaps in skills can be accounted for at different ages using international data from a harmonized dataset.

The skills measured in the PIAAC are Cognitive Foundation Skills (CFS) or "key information-processing skills." This paper focuses on literacy and numeracy skills since problem-solving[6] skills are not available for some of the countries in our reference sample.[7] Firstly, "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*; Secondly, "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*. Each cognitive skill is assessed on a 500-point scale.[8]

An issue worth mentioning is the implication of complex sample design for calculating error variance. The error variance of sample statistics in the PIAAC

[5] The focus of the PIAAC is on certain aspects of literacy, in particular the understanding and use of texts. Writing skills and the ability to produce or format documents are not assessed. This is not because these skills are not considered as important aspects of literacy in broad terms but largely because of the practical difficulties associated with assessing adults' writing in large-scale international surveys.

[6] "Problem solving in technology-rich environments" defined as the ability to use digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks (ICT skills - that is, skills in using information and communications technology).

[7] Problem solving skills are not available for Spain, Italy, France and Chypre.

[8] The objective of the assessments is to describe the level and distribution of the skills of the adult population, not to test the proficiency of individuals. The total number of items used in the assessments is greater than the number answered by any single respondent, each of whom undertakes a subset of the tasks administered.

consists of two components: Sampling variance, which reflects uncertainty due to obtaining a specific sample from the population, and Imputation Variance, which reflects uncertainty due to the random draw of plausible values. The Jackknife Replication Approach was used to calculate replication weights. We use the information provided by the PIAAC on sampling variance and imputation variance to estimate the parameters of interest as well as standard errors.

3 Statistical evidence of gender gaps in cognitive competences

Our baseline sample is composed of native[9] workers aged 24–49. In order to maintain a homogeneous sample when linking skills with gender gaps in labor market outcomes, we restrict our analysis to the 23 countries with information on individual wages. We start our empirical analysis by testing whether there is evidence of gender gaps in cognitive abilities and, if so, describing how they change for different age groups. Individuals enter into the labor market with a particular level of cognitive skills but these levels may change upwards or downwards depending on the individual's particular labor path. For that purpose, our reference sample is divided into three age groups: (1) Entrants into the labor market (aged 24–29); (2) Prime age workers aged 30–39; (3) Prime age workers aged 40–49. Particular attention is paid to the age group that we denote as "entry age" (24–29 years) compared with the next age group (30–39), when motherhood plays an important role for women.[10] Empirical evidence (Kleven et al. 2018 among others) finds a huge increase in the gender gap in labor market participation and earnings, due to the penalty that maternity imposes for women's careers relative to men's. Paul (2008) finds a substantial movement towards part-time work for women that occurs with the first birth and continues steadily for ten years. Gallen et al. (2019) show for Denmark that 30 percent of the gender hours gap can be explained by the sorting of women into lower-hours workplaces. Mothers drive this hour gap, the group for whom differences in employer, occupation, education, and experience also imply large differences in wages. The PIAAC database is purely cross-sectional and it does not permit individual labor market trajectories to be followed. To look at differences in gender gaps in different life cycle phases we study gender gaps in different age groups separately. Note that given the cross-sectional nature of the data, differences encountered across age groups may be due not only to age but also to cohort effects, and they cannot be distinguished. Our primary interest is to study gender differences particularly for the youngest two age groups (24–29 and 30–39), although we will also present those for the oldest group.

[9] We restrict our sample to native workers since results could be distorted by using the full sample for two reasons: Firstly, immigrants might face more problems in answering correctly concerning cognitive skills; secondly, measurement of educational attainment levels can be very different between samples of natives and immigrants.

[10] Gender differences for the oldest group may be due to many unobserved components, such as different trajectories, that our data cannot capture.

Table 1 Gender gaps in cognitive numeracy and literacy skills (overall and by age) all individuals and workers

	Women		Men		Gender gap (%)
	Mean	sd	Mean	sd	
All individuals					
Numeracy					
Aged 24–29	272	47	282	46	−3.68%
Aged 30–39	272	44	283	47	−3.87%
Aged 40–49	263	46	275	50	−4.65%
Overall	268	46	280	48	−4.20%
Literacy					
Aged 24–29	285	42	286	43	−0.21%
Aged 30–39	283	42	285	44	−0.54%
Aged 40–49	273	42	275	45	−0.69%
Overall	280	43	281	44	−0.59%
Workers					
Numeracy					
Aged 24–29	276	45	283	46	−2.40%
Aged 30–39	275	43	284	46	−3.22%
Aged 40–49	265	44	276	49	−4.10%
Overall	271	44	280	48	−3.49%
Literacy					
Aged 24–29	288	41	286	42	0.76%
Aged 30–39	285	41	285	43	−0.28%
Aged 40–49	275	42	276	45	−0.59%
Overall	281	42	282	44	−0.27%

PIAAC individual sample weights are considered. These math and literacy scores are the mean of the corresponding ten plausible values. The sample of workers refers to individuals who are currently working or unemployed

3.1 Gender gaps in cognitive skills by age

Sample statistics displayed in Table 1 motivates the analysis by examining how numeracy and literacy skills vary by gender and across ages. It depicts mean literacy and numeracy test scores measured on a 500-point scale for all individuals and for current workers, respectively.[11] The first point to note is that women exhibit lower competency levels in numeracy skills. On average, the gap for all individuals is 4.2% (12 points on the 500 scale) and as expected, it is somewhat smaller for the sample of

[11] To interpret these statistics appropriately, note that in PIAAC each area of cognitive skill is a latent variable that is estimated using item-response-theory models (see OECD 2013 for details). The database PIAAC provides 10 plausible values rather than only one individual score for each respondent and each skill domain. Using the average of the 10 plausible values provides an unbiased estimate of individual skills in each domain. The sample statistics shown in Table 1 use this average, which uses the weights provided by the PIACC to control for sampling variance that reflects uncertainty due to obtaining a specific sample from the population.

workers at 3.5% (9 points on the 500 scale). This difference in gender gaps between the whole sample and the employed population points to some kind of positive sorting into the labor market for women. For the two groups of individuals, the pattern by age is very similar. This reinforces the interest in understanding the link between cognitive abilities and gender gaps in different areas of labor market performance by age groups. The gap already exists at age of entrance into the labor market (−3.7% in the 24–29 age group), and reaches a maximum of −4.6% in the 40–49 age group. This evidence is striking when one considers that females either systematically outperform males or have made enormous gains on many educational dimensions.[12]

With respect to literacy, however, the picture is rather different. On average, men and women score very similarly so there are not relevant gender gaps on average for the full sample (from −0.21 to −0.69%) neither for the sample of workers. Only there is a positive gap (in favor of women) for the sample of young workers more attached to the labor market (0.76%).

Other interesting feature is that from age 40 onwards both men and women obtain lower scores in both literacy and numeracy skills and this drop is slightly smaller for the subsample of workers. For instance, for the sample of workers, scores in maths drop by 3.6 and 2.7% for females and males respectively from age 30–39 to the following age group. This is likely to be primarily an age rather (i.e., differences in labor market path through the life cycle) than a cohort effect. For instance, Green and Riddell (2013) document a cohort-level fall in literacy after age 45, suggesting that skills suffer obsolescence over the lifecycle. And the larger drop in math scores for females versus males between this two age groups could be related to gender differences in labor market paths. Thus, Jimeno et al. (2016) shows that the number of years of working experience correlates with performance in PIAAC mainly because on-the-job learning to contributes to skill formation. Moreover, a look at gender differences in numeracy and literacy skills from the different PISA waves shows gender gaps to be surprisingly stable across the different waves, and hence across the different cohorts (at least at the age of 15). Unfortunately, we have no evidence from different waves for the PIAAC that could provide additional support regarding the importance of cohort effects at older ages.

3.2 Gender gaps in cognitive skills by educational level and fields of study

A second interesting question to address is whether gender gaps in cognitive competencies vary depending on the attained level of education and on the selected area of study. It is true that in recent decades we are witnessing, in most developed countries, a massive influx of women into higher education, mostly university. This phenomenon has contributed positively to the reduction of gender gaps in labor participation rates and wages. However, on average, the areas of study primarily chosen by women are those related to health, education and humanities. The female presence in STEM (Science, Technology, Economics and Maths) areas is very scarce

[12] In many OCDE countries, there are more graduating females from four-year colleges than males (Goldin et al. 2006). Additionally, the high school dropout rate tends to be lower for females compared to males.

Table 2 Cognitive skills in literacy and numeracy by educational levels

	Women				Men				Gender gaps	
	Numeracy		Literacy		Numeracy		Literacy		Numeracy	Literacy
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d		
All individuals										
Primary	201	49	220	44	215	47	223	42	−6.76%	−1.14%
Secondary	253	43	265	40	265	44	267	41	−4.59%	−0.68%
Post-compulsory secondary	281	35	293	34	288	38	290	36	−2.53%	1.09%
University	295	37	303	35	313	36	312	33	−5.68%	−2.79%
Workers										
Primary	211	50	225	45	219	47	226	42	−4.01%	−0.49%
Secondary	257	42	267	39	267	44	269	41	−4.00%	−0.58%
Post-compulsory secondary	281	35	292	34	289	37	291	35	−2.94%	0.40%
University	296	37	303	34	313	36	312	33	−5.77%	−2.87%

PIAAC individual sample weights are considered. These math and literacy scores are the mean of the corresponding ten plausible values. The sample of workers refers to individuals who are currently working or unemployed

in most countries—no higher than 25%, and in fact, the goal of increasing the presence of women in higher education in STEM areas is now on the agenda of most national and international institutions.

Table 2 provides descriptive evidence of gender gaps in literacy and numeracy competences for low, medium and highly educational levels. The last column of Table 2 shows the share of women in each education group. For both skill dimensions, gender gaps are highest among men and women with basic studies. For numeracy skills, the gap for individuals with primary studies is over 6%, it is lowest for those with post-secondary studies (2.9%) and for highly educated men and women, and female disadvantage rises again over 5.6%. On the contrary, for literacy skills, there is a similar gender gap between men and women with medium and low educational levels. This gender gap in literacy become relevant only for individuals with university studies. At any rate, the gap is much smaller than that of numeracy skills—around 2.7%. Focusing only on workers, the pattern is slightly different. Gender gaps in maths decrease when comparing men and women with low educational attainment (−4.0%), whereas they remain very similar if we restrict to workers with highly educational attainment (−5.7%). Henceforth, the selection process into employment seems to be more important for women with low educational levels than for men or women with high educational levels. Similar pattern is found for literacy skills for workers—very low gender gaps when considering low educated men and women, but very similar gaps when restricting to highly educated working individuals.

We have shown that gender gaps in math skills are important for highly educated workers. One primary reason for this fact could be related to individual's choice on areas of study. Young men and women still tend to choose different fields of study and work—highly educated girls are much more likely to opt for fields of study such as education, health issues, or arts and humanities while they stay behind boys in

Table 3 Cognitive skills in literacy and numeracy by field of study

	Women				Men				% Women	Gender gaps	
	Maths		Literacy		Maths		Literacy			Maths	Literacy
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d			
All individuals											
General programe	249	48	263	45	256	49	261	46	51.29%	−2.81%	0.53%
Humanities	281	40	294	39	289	43	295	40	71.50%	−2.95%	−0.35%
Social science	282	39	291	37	302	38	303	35	56.53%	−6.76%	−4.08%
Science	282	42	286	38	292	43	289	40	22.50%	−3.49%	−0.81%
Agriculture	274	43	278	39	278	44	278	42	33.99%	−1.41%	−0.03%
Health	269	42	281	39	274	46	278	42	70.67%	−1.80%	0.94%
Workers											
General programe	254	46	266	43	260	47	264	45	42.91%	−2.10%	0.60%
Humanities	281	40	294	38	290	43	296	40	67.58%	−3.03%	−0.62%
Social science	284	39	292	37	303	38	303	35	52.96%	−6.36%	−3.78%
Science	286	42	289	39	293	43	290	40	18.81%	−2.53%	−0.33%
Agriculture	279	42	282	38	279	44	279	42	30.11%	−0.11%	1.16%
Health	271	41	282	38	276	45	280	41	67.17%	−1.76%	0.79%
Subsample from workers: highly educated											
General programe	305	32	309	30	307	32	311	32	33.61%	−0.42%	−0.57%
Humanities	289	37	301	36	302	34	309	32	66.95%	−4.30%	−2.57%
Social science	296	36	303	35	310	36	310	33	45.44%	−4.59%	−2.46%
Science	307	36	308	33	321	35	315	32	24.47%	−4.56%	−2.40%
Agriculture	308	30	308	28	312	31	311	29	38.84%	−1.53%	−0.84%
Health	293	35	299	33	308	41	307	37	64.13%	−4.97%	−2.59%

PIAAC individual sample weights are considered. These math and literacy scores are the mean of the corresponding ten plausible values. The sample of workers refers to individuals who are currently working or unemployed. Humanities includes: teacher training and education science, humanities, languages and art; social science includes social science, business and law; science includes science, mathematics and computing, engineering, manufacturing. Agriculture includes: agriculture and veterinary; health includes: health and welfare services

mathematics, engineering and computer sciences (OECD, 2015a). Table 3 presents gender gaps in numeracy and literacy skills by field of study for all individuals, as well as for some subsamples: all workers and workers with university education, which presumably are more homogeneous. One column of Table 3 also includes the percentage of women by areas of study (% Women) showing that, as expected, there is gender segregation by areas of study, women tend to prefer humanities or health (around 70%), and men prefer science (around 78%). In addition, math skills are highest for the subsample of highly educated workers, as expected, for all fields of study. Across fields, math skills are highest for Social Sciences and Sciences for men independent of their labor status. For women, math skills show smaller differences across fields, although Science appears the field of study with highest values, primarily for the highest educated group. The positive correlation between math skills and field of study with more contents in maths will be clearer in Table 4, where math skills are estimated against educational levels and field of study.

The first result to be noted is that in all fields of study and for all different groups, gender gaps in maths are remarkable. They range from −1.8% in health where

Table 4 Gender gaps in math skills—adjusted by individual characteristics (sample age 24–49)

Sample	All individuals			Employed			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Women	−0.040*** (0.00)	−0.045*** (0.00)	−0.032*** (0.00)	−0.033*** (0.00)	−0.042*** (0.00)	−0.029*** (0.00)	−0.026*** (0.00)
Education (ref: primary)							
Secondary		0.219*** (0.01)	0.192*** (0.01)		0.183*** (0.01)	0.158*** (0.01)	0.156*** (0.01)
Post-compulsory secondary		0.303*** (0.01)	0.258*** (0.01)		0.261*** (0.01)	0.222*** (0.01)	0.220*** (0.01)
University		0.375*** (0.01)	0.324*** (0.01)		0.331*** (0.01)	0.287*** (0.01)	0.286*** (0.01)
Field of study (ref: general program)							
Humanities			0.037*** (0.00)			0.028*** (0.00)	0.027*** (0.00)
Social science			0.060*** (0.00)			0.050*** (0.00)	0.049*** (0.00)
Science			0.076*** (0.00)			0.068*** (0.00)	0.066*** (0.00)
Agriculture			0.037*** (0.00)			0.028*** (0.01)	0.029*** (0.01)
Health			0.020*** (0.00)			0.012*** (0.00)	0.010*** (0.00)
Age		X	X		X	X	X
Labor market characteristics							X
Sample	68,169	68,169	68,169	53,151	53,151	53,151	53,014
R2	0.158	0.342	0.361	0.181	0.321	0.339	0.344

Standard errors between brackets. All models include country fixed effects. Labor market characteristics refer to type of contract (permanent versus temporary), full-time contract, firm's size (Big Firm with more than 200 employees and private firm) and type of occupation (nine groups)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

women representation is high (reaching 70%), to −6.7% in social science, where women are also majority (56.5%). A similar pattern is found when the analysis is restricted to the sample of workers. Gender gaps in maths decrease slightly when looking at the sample of individuals with university studies. Still, gender gaps in maths are remarkable (around 4–4.5%) in fields of study which are quite analytical, such as social science and science. For the rest of the fields and for this subsample, the gaps range from 4.3% in humanities to 4.9% in health. Second, if we look at the relationship between the degree of feminization of fields and math scores, the higher the degree of field feminization, the lower the score in maths.[13] Health and Humanities, which are highly feminized fields, score lower than Science, which is the most masculine field. Henceforth, results confirm that there are gender gaps in cognitive skills even within men and women who chose similar fields of studies, and, within more analytical fields, such as science or social science.

3.3 Gender gaps in cognitive skills by occupation

Studies of gender gaps often highlight the importance of occupational segregation in understanding the behavior of the pay gap. Men and women occupy different jobs and this occupational segregation explains part of the observed wage gap. It is therefore relevant to document, similarly as it has been done within specific areas of study, whether there are occupational segregation and whether there are disparities in gender differences in skills within each occupation. Table 5 presents such descriptive evidence. Occupations have been disaggregated to 1-digit classification (nine occupational groups). Two results are worth noting: First, occupational segregation is meaningful: Women are overrepresented in Professionals, clerks, service workers and elementary occupations, whereas they are clearly underrepresented in occupations such as legislators, machine operators and craft workers. Second, occupational feminization seems to be positively associated with below average math scores. Third, as with fields of studies, we find a negative correlation between gender gaps in math skills and the degree of feminization of an occupation.[14]

3.4 Gender gaps in cognitive skills across countries

Given the disparity of many of the countries under analysis, we also present gender gaps in math and literacy skills across the countries under analysis. Figure 1 displays such differences. The first issue to highlight is that math scores for women are always lower than those of men and henceforth, gender gaps in maths skills are present in all countries. On the other hand, literacy scores for women are higher than those for men and henceforth gender gasp in literacy are not observed in all countries and whenever they exist, they tend to be much lower than those of math skills.

[13] Using cross country variation, we obtain that the correlation between the degree of field feminization of fields of studies and math scores is −39%

[14] Using cross country variability, we obtain that the empirical correlation between the degree of occupational feminization and the gender gap in numeracy skills within each occupational group is around −12%

Table 5 Gender gaps in cognitive skills by occupations {sample of workers}

	Women				Men				Gender gaps		Women
	Maths		Literacy		Maths		Literacy		Maths	Literacy	
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	(%)	(%)	(%)
Legislators	289	39	296	35	305	41	301	39	−5.18%	−1.67%	29.00%
Professionals	293	37	300	35	311	38	310	35	−5.97%	−3.34%	51.66%
Technicians	283	38	290	36	295	40	294	37	−4.19%	−1.30%	43.04%
Clerks	279	37	289	36	286	42	288	39	−2.51%	0.46%	64.66%
Service workers	259	42	271	40	275	44	279	40	−5.99%	−3.06%	61.23%
Skilled agriculture/fishery	257	46	266	44	253	51	257	49	1.53%	3.40%	22.66%
Craft	255	49	266	47	265	43	266	42	−3.98%	0.10%	11.45%
Machine operators	249	41	259	41	261	45	264	42	−4.53%	−1.83%	15.26%
Elementary occupations	232	46	247	44	245	49	252	43	−5.52%	−1.87%	52.31%

PIAAC individual sample weights are considered. These math and literacy scores are the mean of the corresponding ten plausible values. The sample of workers refers to individuals who are currently working or unemployed. Legislators include legislators, senior officials, and managers; technicians include technicians and associate professionals; service workers include, services workers and shop and market sales workers; craft includes craft and related trades workers; machine operators include plant and machine operators and assemblers

3.5 Adjusted gender gaps in math skills

Until now, we have provided clear evidence of the existence of gender gaps in maths skills by different individual and labor market characteristics, whereas gender gaps in literacy skills barely emerge. Now we explore in more detail gender gaps in math skills using simple linear regressions and factoring in several individual characteristics, including educational level, age and field of study. Additionally, for workers, we also adjust for other labor market characteristics, such as the type of contract and hour schedule and size and type of firm. Results are presented in Table 4 for all individuals (columns 1–3) and for the sample for workers (columns 4–7). Results indicate that for all individuals, the adjusted gender gap in math skills, once not only educational attainment but also field of study is controlled for decreases in about 1 percentage point (or around 20% in relative terms), from 4.0 (column 1) to 3.2% (column 3). In accordance with previous statistical evidence, the adjusted gender gap in math skills slightly increases when only controlling for education level from 4.0 (column 1) to 4.5% (column 2). Henceforth, the contribution of fields of study to understand gender gaps in math skills is around 1.3 percentage points (or around 28% in relative terms), since the adjusted gap drops from 4.5 (column 2) to 3.2% (column 3). For workers the adjusted gender gap in math skills in smaller than for the full-sample signaling a positive sorting into the labor market for higher skills women. For this sample, if age, educational attainment and field of study are factored in, the adjusted gender gap falls from around 3.3 to 2.9%. If, additionally, we condition for labor market covariates such as type of contract, size of firm and occupation, the gender gap in math skills decreases slightly, but it is still over 2.6%. Hence, the conclusion reached so far is that whereas differences in field of study and other labor

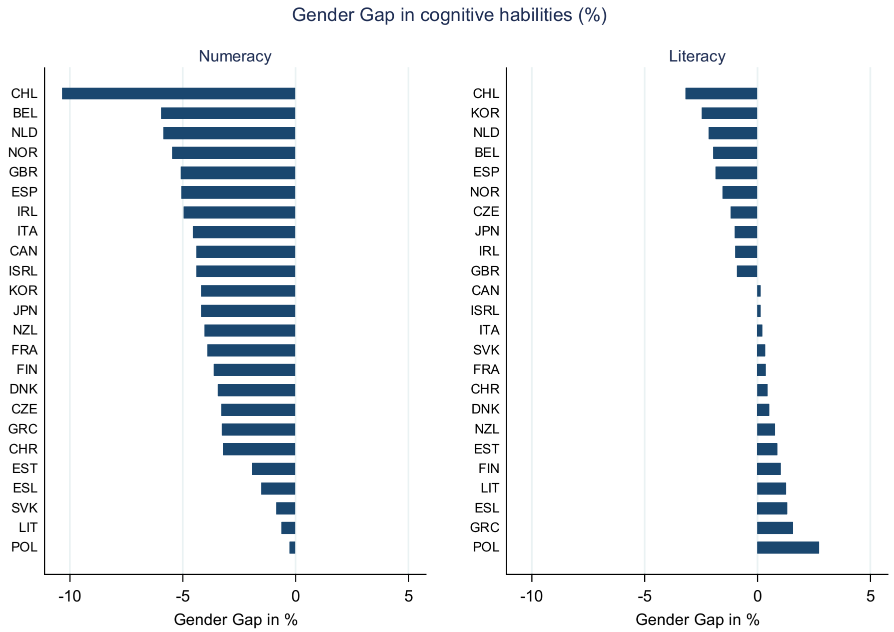

Fig. 1 Gender gaps in cognitive skills by countries (full sample). PIAAC individual sample weights are considered. These math and literacy scores are the mean of the corresponding ten plausible values. Countries are ranked in descending order of the gender gaps in scores

market variables may be part of the factors underlying gender gaps in math skills, there is still a considerable fraction of it that remains even within similar jobs and within the same field of study. Although not reported for the sake of space, if we run similar gender gaps estimation for the "entrance age" group, for which we might anticipate lower differences in adjusted skill gaps and scores are less related to heterogeneous labor market paths, the pattern is very much the same.[15] Finally, coefficient estimates from educational levels and fields of study confirm some of the ideas already presented in the statistical section. They are, firstly, math skills are positively correlated with the level of studies and secondly, by field of studies, studying social science and Science is positively correlated with higher scores in math skills.

4 From gender gaps in skills to gender gaps in labor market outcomes

4.1 Empirical approach

To examine the link between gender gaps in skills and gender gaps in labor market outcomes (Y_i), we start with a standard reduced form estimation where we assume that for each individual i, labor market outcome Y_i (labor market participation or log

[15] Results available from authors upon request.

wages, in our case) can be described as a function F on a set of covariates (H_i). These covariates include some measures of human capital, such as educational attainment and age, as well as other variables that are known to affect labor market outcomes, such as the presence of children in the household, individual's health situation, having a couple, the labor market attachment of the partner and whether the individual is first or second immigrant generation. Gender gaps are captured by an indicator of gender, which takes the value of one if the respondent is female and zero if male. Thus, the general specification of the model to be estimated is as follows:

$$Y_i = F\left\{ \propto + \beta\, Female_i + \sum_{j=1}^{k} \delta_i H_i \right\} + \varepsilon_i \tag{1}$$

Depending on the particular labor market outcome $\{Y_i\}$ the function F() will differ. In particular, it will be a non-linear function (discrete choice models for Y_i representing labor market participation) or a log-linear function of the observed characteristics (for the Y_i representing log-wages. The coefficient $\{\beta\}$ shows the adjusted gender gap in the corresponding labor market outcome conditional on the same observed human capital levels as well as other individual and family characteristics. We then expand this basic specification (1) to include a more direct measure of cognitive skills (CS) (in particular, numeracy skills) to check if it shows predictive power for the estimation of labor market outcomes, Y_i. We are also interested in measuring the extent to which the adjusted gender gap in labor market outcomes found in the basic specification (β) changes when math skills are factored in, or in other words, the estimated gender wage gap, (β'), conditioned on the same math skills:

$$Y_i = F\left\{ \propto' + \beta'\, Female_i + \gamma CS_i + \sum_{j=1}^{k} \delta_i' H_i \right\} + \varepsilon_i' \tag{2}$$

A growing literature shows that even within educational levels, there are statistically significant returns on cognitive skills in terms of labor market outcomes $\{\gamma > 0\}$.[16] Hence, if there are gender gaps in cognitive skills (in favor of men, as we have shown previously) we expect the estimated gender gap $\{\beta'\}$ from Eq. (2) to be smaller than that in Eq. (1), β, as men and women share similar cognitive skills. The difference between the two coefficients reveal the association between gender gaps in labor market outcomes and cognitive skills.

4.2 Taking into account motherhood

In most developed countries, a disproportionate burden is placed on women to provide unpaid care in the home—women provide 3.1 times the care work of men. This affects their decisions with respect to their labor supply, affects their human

[16] Hanushek et al. (2015) use individual information on numeracy cognitive skills from the PIAAC to account more precisely for the size of the returns on skills for wages and conclude that a one-standard-deviation increase in numeracy skills is associated with an 18% increase in wages among prime age workers. Note, however, that their baseline model does not include years of schooling. Hampf et al. (2017) also use the PIAAC to explore several approaches that seek to address potential threats to causal identification of returns on skills in terms of both higher wages and better employment chances.

capital accumulation, and hence affects their labor-market performance in terms of time employed, type of job, wages, and accumulation of skills. For instance, Meurs et al. (2010) conclude that a child has an impact on career interruption and consequently on women's wages. Similarly, Weeden et al. (2016) argue, namely that much of what appears to be a gender wage gap is a gender-specific family gap in pay and that most of it could be explained by factors directly or indirectly related to motherhood.

To factor in children, we estimate an expanded model of Eq. (2) to account for different gender gaps in labor market outcomes depending on parenthood. More precisely,

$$Y_i = F\left\{\begin{array}{c} G\big(\alpha'' + (Female_i * Non - Parent_i)\beta_{wnp} + (men_i * Non - Parent_i)\beta_{mnp} \\ +(Female_i * Parent_i)\beta_{wp}\big) + \gamma' CS_i + \sum_{j=1}^{k} \delta_i'' H_i \end{array}\right\} + \varepsilon_i'' \tag{3}$$

A comparison of the coefficients of *Female*Non-Parent and Men*Non-Parent*, $\{\beta_{wnp} - \beta_{mnp}\}$, captures the estimated gender gap in the corresponding labor market outcome of non-mothers versus non-fathers, conditional on human capital and other variables. Gender gaps between mothers and fathers are defined by the coefficient associated with *Female* Parent* $\{\beta_{wp}\}$. Notice that this specification also enables us to test for the family gap between genders. For instance, the family gap for female is the difference between $\{\beta_{wnp} - \beta_{wp}\}$, whereas for men it is defined by β_{pnp}.

4.3 Results—GG in skills and GG in labor market performance

In accordance with previous empirical literature, our data show substantial gender gaps in the main two outcomes of interest. Table 6 displays average gender gaps in

Table 6 Gender gaps in main labor market outcomes

	Women	Men	Gender gap
Labor market participation (% working)			GG (women–men)
All	72.00%	90.90%	−18.90 pp.
24–29	72.76%	86.37%	−13.62 pp.
30–39	68.86%	92.03%	−23.17 pp.
40–49	74.60%	92.05%	−17.45 pp.
Wages (hourly wages)			Average GGW
All	15.37	18.38	−17.89%
24–29	13.82	15.53	−11.64%
30–39	15.71	18.07	−14.05%
40–49	15.78	20.04	−23.90%

Labor market participation refers to the number of individuals observed employed as a proportion of the total labor force. Full time students, retired and disabled individuals are omitted from the analysis. Gender gaps in labor market participation are measured in percentage points (pp.) whereas gender gaps in wages are gender gaps in percentages (%)

Table 7 Gender gaps in main labor market outcomes (by education)

	Women	Men	Gender gap
Labor market participation (% working)			GG (women–men)
Primary	41.7%	70.6%	−0.29 pp
Secondary	67.8%	89.6%	−0.22 pp
Post secondary	73.7%	93.8%	−0.20 pp
University	82.2%	94.7%	−0.12 pp
Wages (hourly wages)			
Primary	10.50	12.98	−18.44%
Secondary	11.69	15.31	−23.6%
Post secondary	14.21	17.55	−19.0%
University	17.89	22.25	−19.5%

Labor market participation refers to the number of individuals observed employed as a proportion of the total labor force. Full time students, retired and disabled individuals are omitted from the analysis. Gender gaps in labor market participation are measured in percentage points (pp.) whereas gender gaps in wages are gender gaps in percentages (%)

Labor Market Participation—measured by the average probability of being employed—and hourly wages for the whole sample and for different ages. On average, the two gaps are large for all age groups. In labor market participation the average gender gap is 18.9 percentage points, that is, labor market participation for women is 18.9 percentage points lower than that for men. This gender gap is lowest for young workers and highest for individuals in the middle age cohort, when maternity takes place. The gender gap in wages is on average 17.8% and it is increasing by age cohorts, from 11.6 to 23.9%.[17]

Further evidence of gender gaps in main labor market outcomes is presented in Tables 7–9. Gaps in LMP and in wages are displayed by educational level (Table 7), by field of study (Table 8) and by Occupation (Table 9). With regards to education, we observe that educational levels strongly influence labor market participation for women and henceforth, gender gaps in Participation decrease steadily with education, as expected. On the contrary, gaps in wages do not seem to follow a particular pattern since they are the lowest for workers with primary studies and the highest for workers with secondary studies.[18]

Concerning fields of study, female participation is highest in Social Sciences, business and law, followed by health, and it is lowest in General Program, which probably embeds a high variety of level of studies. Gender gaps in participation are

[17] For wages, we use pre-tax earnings which has the advantage of capturing how the market rewards certain characteristics before the effect of the tax system is felt. However, it might potentially bias the cross-country comparison of wage dispersion to the extent that different countries differ in the progressivity of their tax systems. In addition, our definition of wages also considers discretionary bonus payments since the unexplained part of the gender wage gap is typically higher and this is typically related to more qualified jobs or jobs where skills might play a major role.

[18] The reason for this result is that wages for women with primary and secondary studies are very similar. Nevertheless, standard deviation in wages for secondary studies is much higher than for primary studies.

Table 8 Gender gaps in main labor market outcomes (by field of study)

	Women	Men	Gender gap
Labor market participation (% working)			GG (women–men)
General program	61.3%	85.8%	−0.25
Teacher training, education, humanities, languages, and arts	74.9%	90.1%	−0.15
Social sciences, business, and law	82.0%	94.7%	−0.13
Science, mathematics, Computing, Engineering	74.8%	93.8%	−0.19
Agriculture and veterinary	78.0%	93.2%	−0.15
Health and welfare services	77.3%	91.1%	−0.14
Wages (hourly wages)			
General program	11.30	15.19	−25.6%
Teacher training, education, humanities, languages, and arts	15.45	19.71	−21.6%
Social sciences, business, and law	15.76	21.46	−26.5%
Science, mathematics, computing, engineering	15.43	18.04	−14.5%
Agriculture and veterinary	12.31	16.44	−25.1%
Health and welfare services	14.54	16.91	−14.0%

Labor market participation refers to the number of individuals observed employed as a proportion of the total labor force. Full time students, retired and disabled individuals are omitted from the analysis. Gender gaps in labor market participation are measured in percentage points (pp.) whereas gender gaps in wages are gender gaps in percentages (%)

primarily driven by female participation, since except for General Program, male participation is over 90% in all fields of study. Regarding wages, firstly, it is interesting to note that hourly wages differ between fields of study more for women and for men. Secondly, across all fields of studies men benefit from higher hourly wages than women. Gender gaps are highest in social Sciences, business and law (and in General Program) and lowest in health and welfare services, where, as reported in Table 3, more than 70% are women.

Finally, Table 9 reports gender gaps in wages by occupation, and reveals that gender gaps are highest in some manual (and masculine) occupations, such as craft and related trade workers and plant and machine operators, where gender gap in hourly wages is over 24%. Among white-collar occupations, gender gaps are highest among the least qualified jobs, i.e., service workers, where gaps in hourly wages is over 30%. On the contrary, for highly qualified white-collar jobs, such as legislators, Professionals and Technicians, gender gaps in wages are around 15–18%.

4.4 Gender gaps: math skills and labor market participation

Gender differences in experience and labor force attachment have been seen as central to the understanding of the gender wage gap. Moreover, our statistical analysis has concluded that gender gaps in cognitive skills may differ between the whole sample versus the subsample of workers pointing out to some degree of sorting. For that reason, we proceed to test the link between gender gaps in math skills and gender gaps in labor market participation by estimating the probability of being in work (working versus not working) for our sample of 23 OECD countries. We do this on the first place for the whole sample (24–49). In this case, the outcome variable takes

Table 9 Gender gaps in main labor market outcomes (by occupation)

	Women	Men	Gender gap
Wages (hourly wages)			
Legislators	21.43	26.25	−18.36%
Professionals	18.79	22.86	−17.80%
Technicians and associate professionals	15.85	18.72	−15.35%
Clerks	13.35	17.19	−22.30%
Service workers and shop and market sales workers	10.72	15.42	−30.49%
Skilled agricultural and fishery workers	8.88	11.75	−24.43%
Craft and related trades workers	9.74	14.45	−32.60%
Plant and machine operators and assemblers	10.65	14.18	−24.92%
Elementary occupations	9.82	13.05	−24.75%

Labor market participation refers to the number of individuals observed employed as a proportion of the total labor force. Full time students, retired and disabled individuals are omitted from the analysis. Gender gaps in labor market participation are measured in percentage points (pp.) whereas gender gaps in wages are average gender gaps in percentages (%)

value of 1 if the individual works and zero otherwise and henceforth, discrete choice models are used in the estimation (logit model). For these estimates, we use the full sample of individuals, either employed, unemployed or inactive if the reason for inactivity is different to health issues, retirement or full-time studies. Table 10 displays main results—estimated marginal effects and their corresponding standard errors—from several model estimations.[19] All specifications include country fixed effects and other individual covariates such as age, health status and some household characteristics (presence of children and partner labor market status). Column 1 (Model 1) displays the estimated gender gap in LMP adjusting additionally for educational attainment, and hence, estimating gender gaps in LMP within educational attainment. Column 2 (Model 2) adds math scores to the previous estimation. Column 3 (Model 3) presents the gender gap adjusted for educational attainment and field of study (but not adjusted by math scores), and finally, column 4 (Model 4) reports estimated gender gaps in LMP adjusted by cognitive math skills, educational attainment and field of study, i.e., gender differences in LMP between men and women within the same cognitive math skills and within the same field of study. Detailed results for reference models are added in Appendix (Table 19).

Results from the estimation of these three models reveal the following interesting results: First, gender gaps in labor market participation are substantial even between men and women with the same standard measures of human capital, such as age and education, and even within the same field of study. The adjusted gender gap, once all

[19] Retired individuals and full-time students are excluded from the sample. The main sample statistics for all covariates are presented in Table 17 in the Appendix.

Table 10 Gender gaps in labor market participation and cognitive skills (employment probability, marginal effects)

	Full sample: 24–49			
	(1)	(2)	(3)	(4)
Math scores	–	0.0099*** (0.00)		0.0092*** (0.00)
Women	−0.182*** (0.01)	−0.170*** (0.01)	0.177*** (0.01)	−0.168*** (0.01)
Education (ref. primary)				
Secondary	0.153*** (0.01)	0.113*** (0.01)	0.126*** (0.01)	0.095*** (0.01)
Post-compulsory secondary	0.203*** (0.01)	0.143*** (0.01)	0.152*** (0.01)	0.106*** (0.01)
University	0.258*** (0.01)	0.177*** (0.01)	0.206*** (0.02)	0.142*** (0.02)
Field of study (ref. general studies)				
Humanities			0.023** (0.01)	0.015 (0.01)
Social science			0.082*** (0.01)	0.068*** (0.01)
Science			0.060*** (0.01)	0.042*** (0.01)
Agriculture			0.066*** (0.02)	0.057*** (0.02)
Health and welfare			0.058*** (0.01)	0.054*** (0.01)
Sample	63,829	63,829	63,829	63,829

Dependent variable: binary indicator of whether the individual is employed (=1) and 0 otherwise. Estimation takes into account PIAAC sample and replication weights. Numeracy scores are divided by 10. Marginal effects are displayed with their jackknife standard errors in brackets. All specifications include country fixed effects and other individual characteristics such as age, educational attainment level (four groups), fields of study (six groups), health status (binary indicator), and households characteristics such as the presence of children (binary indicator), leaving with a couple (binary indicator), partner's attachment to the labor market (binary indicator), and first and second generation immigrant (binary indicator). The regression sample includes all individuals except those retired or exclusively involved in formal education

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

covariates are included as controls (Column 4), amounts to 16.8 percentage points, i.e., the probability of working is 16.8 percentage points lower for women than for men with similar observed characteristics in terms of education level, field of study, age, and health and family status. Second, math scores are positively associated with the labor market participation decision. This is the expected result, as opportunity costs from not participating in the labor market—i.e wages—are higher the higher are the skill levels of workers. In particular, a one standard deviation increases in math scores (around 45 points) is associated with an overall increase in the probability of working of about 4.1 percentage points.[20] Third, math scores contribute to explain a portion of the adjusted gender gap in labor market participation, but this gap still remain. When we compare gender gaps in columns 2 and 1, that is, without field of study, the contribution of math skills to the adjusted gender gap is 1.2 percentage points (or 6.6% in relative terms). When field of study is factored in, the contribution is then slightly smaller, 0.9 percentage points (or 5.1% in relative terms). This result is extracted from the comparison between the estimated gender gap in columns 4 and 3, whose difference is the result of factoring in math scores in the

[20] In the estimation, math scores have been divided by ten, henceforth, to compute this effect we have to multiply the estimated marginal effect by 4.5 points instead of 45 points. This must be taken into account along the rest of the paper.

labor market participation estimation. The contribution of gender gaps in maths skills into gender gaps in labor market participation is not high, but, interestingly it is higher than other potential drivers of the gender gap, such as field of study, whose contribution can be measured comparing the gaps of columns (1) and (3) and it amounts to 0.5 percentage points (or 2.7% in relative terms)[21]. Finally, it is also interesting to see that when math scores are factored in, the association between university studies and labor market participation decreases substantially. This also happens when looking to fields of study related to science. This is an expected result, as it has previously observed that there is a positive correlation between math scores and educational level. If math scores are omitted from the regression, part of its effect is likely to be captured by educational attainment, as results indicate.

We now proceed to estimate the probability of working separately by age: 24–29 (entry age), 30–39 (entry into maternity) and 40–49 (mature or older). The first panel presents the estimation of the probability of working and its correspondent gender gap including as covariates standard educational covariates, field of study, whose coefficients are reported, and other non-reported controls, such as age, health status, the presence of children and the partner's labor market situation. All estimations include country fixed effects. The second panel adds to the previous model math cognitive skills, so as to compare the change in the gender gap in LMP when math cognitive skills are factored in.

The higher panel of Table 11 presents a gender gap in labor market participation which reaches 9.9 percentage points at entrance age, rises to 21.3 percentage points for the "maternity" interval age, and decreases slightly for adults older than 30 years old (17.9 percentage points). As expected, higher educational attainment increases labor market participation and its effect is higher for older cohorts. Finally, labor market participation is highest if the field of study is Social Science, health and to a lesser extent Science (relative to General Studies). This is so for all age groups, though for the youngest ones, filed of study play a minor role. The second estimation, reported in the lower panel of Table 11, factors in Math scores relative to the previous estimation. As expected, math scores and labor market participation are positively correlated and this correlation decreases by age groups: An increase in one standard deviation in math scores is associated with[22] a 4.86 percentage points, 4.63 percentage points, and 3.24 percentage points, increase in the decision to work for each age group, respectively. Secondly, the adjusted gender gap in labor market participation decreases when math scores are factored in, which is the result of the lower math scores exhibited by women, and which has been extensively documented in the first part of the paper. Once we compare men and women with the same math scores, gender gaps in labor market participation decrease, as a fraction of such gap is due to the lower female math skills. Such comparison reveals a (statistically significant) decrease in gender gaps at all ages, and relatively higher for the youngest

[21] This result is extracted from the comparison between the estimated gender gap in columns 1 and 3 of Table 10. The contribution of the field of study is even smaller when comparing adjusted gender gaps when math skills are considered (columns 2 and 4)

[22] Remember that to obtain these marginal effects we multiply the value of the one standard deviation in math scores (4.5) with the estimated marginal effect for each corresponding age cohort (1.08, 1.03 and 0.72)

Table 11 Gender gaps in labor market participation and cognitive skills by age cohorts (employment probability, marginal effects)

	By age cohort		
	24–29	30–39	40–49
	(1)	(2)	(3)
Model 1: baseline model			
Math scores	–	–	–
Women	−0.0999*** (0.01)	−0.213*** (0.01)	−0.179*** (0.01)
Education (ref. primary)			
Secondary	0.106*** (0.03)	0.116*** (0.02)	0.126*** (0.02)
Post-compulsory secondary	0.179*** (0.03)	0.139*** (0.02)	0.131*** (0.02)
University	0.165*** (0.03)	0.204*** (0.02)	0.200*** (0.02)
Field of study (ref. general studies)			
Humanities	−0.0014 (0.02)	0.0307** (0.01)	0.0336** (0.02)
Social science	0.0553** (0.02)	0.0929*** (0.02)	0.0852*** (0.02)
Science	0.0332* (0.02)	0.0826*** (0.01)	0.0534*** (0.01)
Agriculture	−0.0218 (0.04)	0.0998*** (0.02)	0.0887*** (0.02)
Health and welfare	0.0518** (0.02)	0.0632*** (0.01)	0.0564*** (0.01)
Model 2: +observed math scores			
Math scores	0.0108*** (0.00)	0.0103*** (0.00)	0.00723*** (0.00)
Women	−0.0949*** (0.01)	−0.204*** (0.01)	−0.172*** (0.01)
Education (ref. primary)			
Secondary	0.0711*** (0.03)	0.0800*** (0.02)	0.101*** (0.02)
Post-compulsory secondary	0.129*** (0.03)	0.0861*** (0.02)	0.0956*** (0.02)
University	0.0923*** (0.03)	0.129*** (0.03)	0.151*** (0.02)
Field of study (ref. general studies)			
Humanities	−0.0079 (0.02)	0.0228* (0.01)	0.0263 (0.02)
Social science	0.0413* (0.02)	0.0774*** (0.02)	0.0723*** (0.02)
Science	0.0138 (0.02)	0.0637*** (0.01)	0.0391*** (0.01)
Agriculture	−0.0271 (0.04)	0.0879*** (0.02)	0.0829*** (0.02)
Health and welfare	0.0457** (0.02)	0.0585*** (0.01)	0.0534*** (0.01)
Sample	15,995	23,603	24,231

Dependent variable: binary indicator of whether the individual is employed (=1) and 0 otherwise. Estimation takes into account PIAAC sample and replication weights. Numeracy scores are divided by 10. Marginal effects are displayed with their jackknife standard errors in brackets. All specifications include country fixed effects and other individual and households characteristics such as age (years), health status (binary indicator), the presence of children (binary indicator) having a couple (binary indicator), partner's attachment to the labor market (binary indicator), and first/second immigrant generation (binary indicator). The regression sample includes all individuals except those retired or exclusively involved in formal education

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

cohort. In particular, for young workers, the gender gap drops from 9.99 percentage points to 8.92 percentage points (a drop of 1.07 percentage points in absolute terms or 10.8% in relative terms), for the 30–39 age group the labor market participation gap drops from 21.3 percentage points to 20.4 percentage points (a drop of 0.9 pp. or

4.2% in relative terms) and from 17.9 percentage points to 17.2 percentage points (a drop of 0.7 pp. or 3.9% in relative terms). The decrease in gender gaps for the youngest cohort is quite significant, and confirms that particularly for young workers, differences in math skills between men and women help to understand a portion of the observed gender gaps in labor market participation. For other age groups, other factors, apart from human capital endowments, seem to play a more prominent role.

Thirdly, we look for differences in gender gaps in Labor Market Participation and its association with math skills for different family situations. There is broad evidence that children pose substantial labor penalty in the labor market for women and our purpose is to look into it at different labor market situations: entry age, maternity age and adult age. To do so, we estimate similar models as those presented in Table 11—two panels, without and with math skills included, but now we disaggregate the association between gender and labor market participation by its children status—no children, children. This is done by interacting the gender indicator with the presence of children, as described in Eq. (3). We only report the coefficients of such interactions, as well as the coefficient of math score when corresponding (in the lower panel).

Results are presented in Table 12 but, to better illustrate the results, estimated gender gaps are also represented in Fig. 2. From the estimated marginal effects shown in Table 12 we compute gender gaps in labor market participation separately for parents and non-parents. The first striking result is the difference in gender gaps in labor market participation between parents and non-parents. This confirms that parenthood is a crucial aspect to account for when looking at gender gaps in LMP. From the baseline model (upper panel, math skills not included), the findings indicate that, when there are no children, women exhibit lower labor market attachment than men—around 6.0 percentage points lower rate of labor market participation. And as before, the gender gap is lower at entrance age (around 2.7 percentage points but not statistically significant),[23] increases notably at the age of 30–39 (around 8.5 percentage points) to decrease slightly for the next adult age interval (to 7.4 percentage points). However, possibly the most interesting result is the comparison of men and women in their labor market attachment with the presence of children in the household. For them, gender gaps increase substantially. On average, they amount to 25.4 percentage points, varying from 20 percentage points for older workers to 30 percentage points for the other two age cohorts. The lower panel of Table 12 includes Math scores to the previous covariates. As we saw in Table 10, math scores are positively associated with labor market participation independently of age and family composition.

The second result worth highlighting is the role of math skills in explaining these gender gaps for parents and non-parents separately. Comparing the estimated gender gap in the baseline model (Model 1) with that in Model 2 (where math skills are factored in) a reduction of the estimated gender gap is observed. In both cases, the gap decreases between 0.5 and 1.5 percentage points. Notice that this drop in the

[23] As explained in Section 4.1, this marginal effect is obtained by taking the difference between the marginal effects of the covariates for Men*No Children and Women*No Children. We also tested whether or not this marginal effect was statistically significant, and we concluded that it was not statistically significant at 95% of confidence.

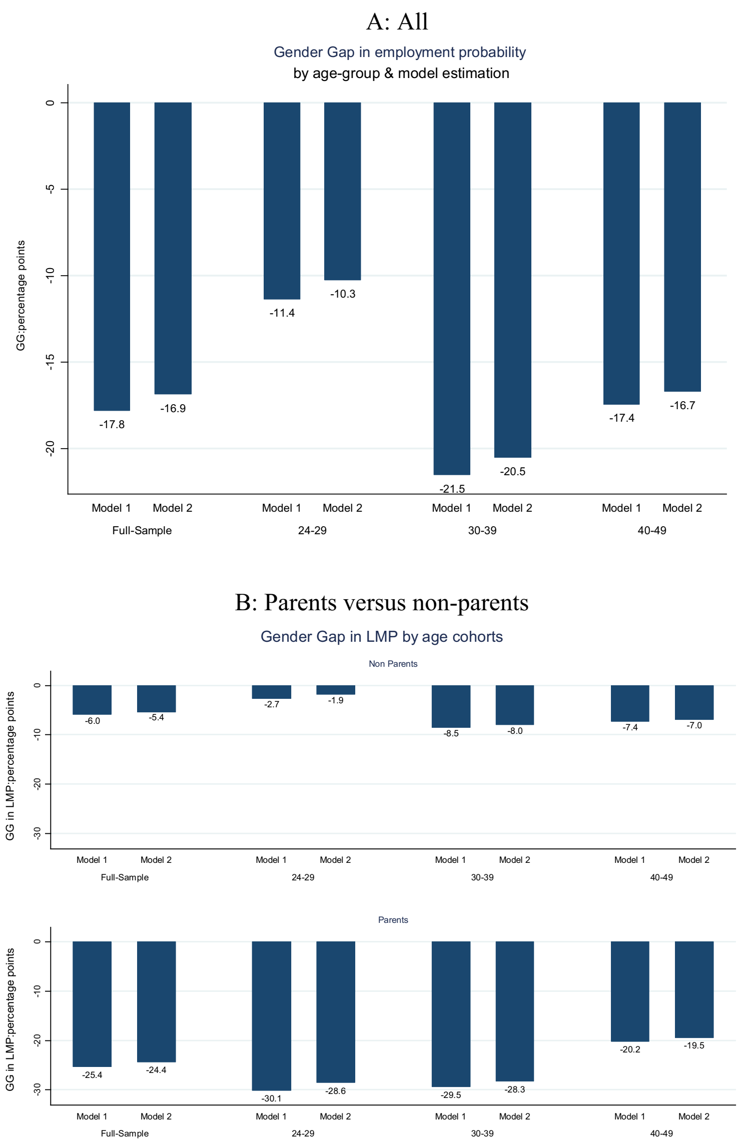

Fig. 2 Adjusted gender gaps in labor force participation (women–men) by age and family type. These are adjusted gender gap computed using coefficient estimates—marginal effects—from Tables 6 (full sample) and 7 (non-parent versus parents). For parents, the adjusted gender gap is the coefficient estimate for women with children since the reference group is men with children. For non-parents, the adjusted gender gap is the difference between the corresponding coefficient estimates for women without children minus coefficient estimates for males without children. For the model without math scores, these adjusted gender gap are −0.060 (se = 0.009), −0.027 (se = 0.015), −0.085 (se = 0.015), −0.074 (se = 0.02) for the full sample, age cohort 24–29, age cohort 30–39, and age cohort 40–49, respectively. For the model with math scores, these estimated gender gaps are −0.054 (sd = 0.009), −0.019 (sd = 0.015), −0.080 (sd = 0.014), −0.070 (sd = 0.02). We have tested whether these gender gaps are statistically different. The results from these adjusted Wald tests lead us to reject the null hypothesis (99% confidence) of equality of gender gaps between these two models—without and with math scores—, for all samples except for age group 40–49 where the null is rejected at 90% confidence

gender gap takes place even controlling for individuals with the same age, educational levels and field of study, just to highlight the most relevant human capital covariates. With respect to the extent to which math skills explain these differences, it is interesting to note that for non-parents aged 24–29 differences in math skills explain 29% of the conditional gender gap (though it is small in absolute terms, 0.8 percentage points). For non-parents in the next age group the introduction of math skills reduces the gender gap in LMP from 8.5 percentage points to 8.0 percentage points (0.5 percentage points or 6.2% in relative terms), which does not account for the whole gap but is nevertheless substantial. Turning to parents, for young individuals differences in math skills are also associated to drops gender gaps in participation (1.5 percentage points or 4.9% in relative terms). And for parents aged 30–39 math skills account for a reduction of 0.9 percentage points in LMP gender gaps, which in relative terms amounts to 4%.[24] In both cases, parents and non-parents, the contribution of math skills to gender gaps in labor market participation for the oldest workers is smaller.

Summarizing, though gender differentials in LMP have decreased in many countries, our results indicate that these gender gaps are still substantial even when comparing men and women with similar human capital endowments in general and with the same educational level and fields of study, in particular. Moreover, gender differences in math skills are positively associated with gender gaps in LMP, particularly for the youngest cohorts, but also for non-parents younger than 40 years. For parents, gender gaps in math skills have a small contribution on the gender gap in LMP. For them, even within the same math skills, additionally to general human capital endowments, gender gaps in participation are substantial, which indicates that other (unobserved) factors determine the differences in labor force participation between mothers and fathers at all ages.

4.5 Gender gaps in math skills and gender wage gaps

To estimate gender gaps in wages and its association to observed gender gaps in math skills we proceed as before. We run a typical log wage regression (all age groups together) as a function of the standard human capital variables such as age, experience and educational attainment (column 1 of Table 13). The estimated wage gender gap reported in column 1 is, therefore, adjusted for such human capital variables. Next, in addition to those variables, we add controls for fields of study, to measure the extent to which gender differences in fields of study contribute to the

[24] These are adjusted gender gap computed using coefficient estimates—marginal effects—from Table 8 (full sample) and 9 (Non-Parent versus Parents). For parents, the adjusted gender gap is the coefficient estimate for women with children since the reference group is men with children. For non-parents, the adjusted gender gap is the difference between the corresponding coefficient estimates for women without children minus coefficient estimates for males without children. For the model without math scores, these adjusted gender gap are −0.060 (se = 0.009), −0.027 (se = 0.015), −0.0854 (se = 0.015), −0.0735 (se = 0.020) for the full sample, age cohort 24–29, age cohort 30–39 and age cohort 40–49, respectively. For the model with math scores, these estimated gender gaps are −0.054 (sd = 0.009), −0.019 (sd = 0.015), −0.0800 (sd = 0.014), −0.070 (sd = 0.020). We have tested whether these gender gaps are statistically different. The results from these adjusted Wald tests lead us to reject the null hypothesis (99% confidence) of equality of gender gaps between these two models—without and with math scores—, for all samples except for age group 40–49 where the null is rejected at 90% confidence.

Table 12 Labor market participation equation: gender gaps in labor market participation (separately for parents and non-parents)

	Full sample	By age cohort		
	24–49	24–29	30–39	40–49
	(1)	(2)	(3)	(4)
Model 1: baseline model				
Math scores	–	–	–	–
Reference men*children				
Men*no children	-0.062^{***} (0.01)	-0.018 (0.02)	-0.0737^{***} (0.01)	-0.0832^{***} (0.02)
Women*no children	-0.122^{***} (0.01)	-0.0457^{*} (0.03)	-0.159^{***} (0.02)	-0.157^{***} (0.02)
Women*children	-0.254^{***} (0.01)	-0.301^{***} (0.02)	-0.295^{***} (0.01)	-0.202^{***} (0.01)
Model 2: +math scores				
Math scores	0.0088^{***} (0.00)	0.0102^{***} (0.01)	0.0097^{***} (0.01)	0.0071^{***} (0.01)
Reference men*children				
Men*no children	-0.0617^{***} (0.01)	-0.0210 (0.02)	-0.0737^{***} (0.01)	-0.0799^{***} (0.02)
Women*no children	-0.116^{***} (0.01)	-0.0401 (0.03)	-0.154^{***} (0.02)	-0.150^{***} (0.02)
Women*children	-0.244^{***} (0.01)	-0.286^{***} (0.02)	-0.283^{***} (0.01)	-0.195^{***} (0.01)
Sample	63,829	15,995	23,603	24,231

Estimation takes into account PIAAC sample and replication weights. Dependent variable: binary indicator of whether the individual is employed (=1) and 0 otherwise. Numeracy scores (observed and predicted) are divided by 10. Marginal effects are displayed and their jackknife standard errors in brackets are on line 2. Marginal effects and predicted probabilities shown represent the mean of individual effects. For interactions of gender with children, the omitted option is "men with children." Detailed estimation results for Model 2 are shown in Appendix Tables 19 and 20. All specifications include country fixed effects and other individual characteristics such as age, educational attainment level, field of study, health status, having a couple, partner's attachment to the labor market and first/second immigrant generation

$*p = 0.10$; $**p = 0.05$; $***p = 0.01$

explanation of gender gaps in wages (column 2). Column 3 reports estimated gender wage gaps once math skills are factored in (but not including fields of study). And finally, column 4 reports gender wage gaps adjusted by the standard human capital variables, fields of study and math skills. Additionally, these four models are re-estimated by adding other labor market controls, such as tenure, occupation, contract type and firm size. Results from this more exhaustive estimation are reported in columns 5, 6, 7 and 8, respectively.[25] Main results are displayed in Table 13. Detailed estimations results are shown in Appendix Table 20 for main reference models.

Firstly, gender gaps in hourly wages amount to 20.6% when we compare men and women within similar standard human capital variables (column 1). If in addition, we factor fields of study (column 2), the gap decreases to 19.1% or in other labor market statistics (column 5), the gap decreases only to 20.1%—i.e., women earn on average 20% less than their male counterparts with similar age, experience and educational levels, and in similar labor market contexts. Secondly, when fields of study and labor market characteristics are factored in (column 6), the adjusted gender wage gap

[25] The main sample statistics for the additional covariates used in the analysis are presented in the Table 18 in the Appendix.

Table 13 Wage equation (log hourly wages): gender gaps in wages—main results

	Full sample: 24–49							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math scores	–		0.0255^{***} (0.00)	0.0246^{***} (0.00)	–		0.0181^{***} (0.00)	0.0178^{***} (0.00)
Women	-0.206^{***} (0.01)	-0.191^{***} (0.01)	-0.177^{***} (0.01)	-0.172^{***} (0.01)	-0.201^{***} (0.01)	-0.194^{***} (0.01)	-0.177^{***} (0.01)	-0.177^{***} (0.01)
Education (ref. primary)								
Secondary	0.202^{***} (0.03)	0.158^{***} (0.03)	0.202^{***} (0.03)	0.0770^{**} (0.03)	0.133^{***} (0.03)	0.110^{***} (0.03)	0.0722^{**} (0.03)	0.0584^{*} (0.03)
Post-compulsory secondary	0.383^{***} (0.03)	0.310^{***} (0.03)	0.383^{***} (0.03)	0.188^{***} (0.03)	0.219^{***} (0.03)	0.180^{***} (0.03)	0.135^{***} (0.03)	0.109^{***} (0.03)
University	0.667^{***} (0.03)	0.590^{***} (0.03)	0.667^{***} (0.03)	0.417^{***} (0.03)	0.408^{***} (0.03)	0.368^{***} (0.03)	0.295^{***} (0.03)	0.269^{***} (0.03)
Fields of study (ref. general studies)								
Humanities	–	0.0360^{**} (0.02)	–	0.0216 (0.02)		0.0183 (0.02)		0.0110 (0.02)
Social science		0.0995^{***} (0.01)		0.0709^{***} (0.01)		0.0706^{***} (0.01)		0.0547^{***} (0.01)
Science		0.106^{***} (0.01)		0.0641^{***} (0.01)		0.0551^{***} (0.01)		0.0294^{**} (0.01)
Agriculture		0.00678 (0.03)		−0.0043 (0.03)		0.0111 (0.03)		0.00191 (0.03)
Health		0.0649^{***} (0.01)		0.0613^{***} (0.01)		0.0386^{***} (0.01)		0.0386^{***} (0.01)
Other covariates								
Age and experience	X	X	X	X	X	X	X	X
Labor characteristics					X	X	X	X
R2	0.407	0.412	0.436	0.438	0.484	0.486	0.498	0.499
Sample	41,138	41,138	41,138	41,138	41,138	41,138	41,138	41,138

Least squares regressions weighted by sampling weights and replication weights are used to compute jackknife standard errors (in brackets). Dependent variable: log gross hourly wage. Numeracy scores are divided by 10. All specifications include country fixed effects and other individual characteristics such as age. Labor characteristics include, labor market experience (years), tenure (years), occupation (nine groups), contract type (fixed-term contract), and firm size (three dummies). Detailed results for the full sample estimation of columns (1)–(3) are shown in Appendix Table 20

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

remains almost the same, which indicates that gender wage gaps cannot be associated to a different specialization of men and women in different fields (conditional on educational level, age and other labor market covariates). Thirdly, there is evidence of a positive association between math skills and wages, even within the same fields of study—an increase of a one standard deviation in math scores (4.5 points) is associated with an increase in hourly wages of around 8–11% (columns 4 and 8). Fourthly, and important for our study, when math scores are factored in the regression, the estimated gender gap in wages decreases by around 2.9 percentage points (around 14% in relative terms) in our baseline model, when fields of study are not included in the model (columns 1 and 3). This drop in the adjusted wage gap is around 1.9 percentage points (or 11% in relative terms) if fields of study are considered (columns 2 and 4). These results indicate, on the first place, that gender differences in math skills contribute more to explain gender wage gaps than fields of study. Secondly, gender gaps in math skills still explain a fraction of the adjusted gender wage gap when comparing individuals within the same age, experience, level of education and field of study and this is due to the lower math skills exhibited by women with respect to men. Nevertheless, this also indicates that there are still unobserved factors which underly gender wage gaps other than difference in cognitive skills.

The next step consists on estimating wage equations separately for different age groups since gender gaps in math skills vary by age groups. The same models of Table 13 are estimated, but for the three different age intervals. Table 14 displays the main results for the estimated gender gap and wage returns for math scores.[26] For an easier visualization of the results, the different gender wage gaps are displayed in Panel A of Fig. 3. This figure shows clearly that adjusted gender wage gaps rise substantially and steadily with ag—from 8.9% at age entry, rise to 18.7% at the "maternity age" and rise again to 23.0% for 40–49 years. When math scores are factored in, the decrease in the gender wage gap is around 1.4 percentage points (or 15% in relative terms), 1.6 percentage points (or 8.5% in relative terms) and 2 percentage points (or 8.6% in relative terms) for young, mature and older workers, respectively. The decrease is significantly different from zero. This is so for all age groups. The association between math scores and hourly wages is, as revealed in Table 14, positive and increasing with the age (an increase in one standard deviation of math scores lead to an increase in hourly wages of 8.9, 9.9 and 12.3% for each age group). An additional feature to be noted from Table 14 is that wage returns to education decrease substantially, particularly at entry ages, when math scores are factored in. As we found for labor market participation, this clearly shows that maths abilities matter for wages directly (i.e., increasing individual's labor market productivity) but also indirectly through fostering higher educational attainment levels.[27]

Finally, given the relevance of family issues for the understanding of gender wage gaps, we provide results from an estimation of these gaps separately for parents and

[26] For sake of brevity, detailed results are not included in the paper but are provided upon request.

[27] We consider this association to be important since it might implied that the estimated contribution of gender gaps in math skills into gender gaps in wages presented in this paper is a lower bound of the true contribution.

Table 14 Wage equation (log hourly wages): gender gaps in wages—main results

	By age cohort		
	24–29	30–39	40–49
Model 1: baseline model			
Math scores	–	–	–
Women	−0.0887*** (0.02)	−0.187*** (0.01)	−0.230*** (0.01)
Education (ref. primary)			
Secondary	0.0204 (0.06)	0.151*** (0.05)	0.171*** (0.04)
Post-compulsory secondary	0.0981 (0.07)	0.326*** (0.06)	0.322*** (0.05)
University	0.260*** (0.07)	0.600*** (0.05)	0.687*** (0.04)
Field of study (ref. general studies)			
Humanities	0.00313 (0.03)	0.0158 (0.03)	0.0615*** (0.02)
Social science	0.0788*** (0.02)	0.0826*** (0.02)	0.106*** (0.02)
Science	0.113*** (0.03)	0.0769*** (0.02)	0.119*** (0.02)
Agriculture	−0.0893* (0.05)	0.0181 (0.03)	0.0235 (0.04)
Health	0.0439* (0.03)	0.0638*** (0.02)	0.0648*** (0.02)
R2	0.313	0.408	0.457
Model 2: +math scores			
Math scores	0.0199*** (0.00)	0.0222*** (0.00)	0.0274*** (0.00)
Women	−0.0753*** (0.02)	−0.171*** (0.01)	−0.210*** (0.01)
Education (ref. primary)			
Secondary	−0.0359 (0.06)	0.0726 (0.05)	0.0847** (0.04)
Post-compulsory secondary	0.0162 (0.07)	0.213*** (0.06)	0.184*** (0.05)
University	0.137** (0.06)	0.439*** (0.05)	0.497*** (0.04)
Field of study (ref. general studies)			
Humanities	0.00245 (0.03)	0.00368 (0.03)	0.0389* (0.02)
Social science	0.0627*** (0.02)	0.0594** (0.02)	0.0691*** (0.02)
Science	0.0887*** (0.03)	0.0398* (0.02)	0.0688*** (0.02)
Agriculture	−0.0723 (0.05)	0.00367 (0.03)	0.00312 (0.04)
Health	0.0425* (0.02)	0.0606*** (0.02)	0.0631*** (0.02)
R2	0.335	0.431	0.486
Sample	10,430	15,254	15,454

Least squares regressions weighted by sampling weights and replication weights are used to compute jackknife standard errors (in brackets). Dependent variable: log gross hourly wage. Sample: employees aged 24–49. Numeracy scores are divided by 10. All specifications include country fixed effects and other individual characteristics such as age and experience. Labor characteristics include labor market experience (years), tenure (years), occupation (nine groups), contract type (fixed-term contract), and firm size (three dummies). Detailed estimation results are upon request

*$p<0.10$; **$p<0.05$; ***$p<0.01$

non-parents. This is done by adding interactions between gender and family situation (children/no children). We follow the same approach used before, i.e., estimate the baseline model, where gender wage gaps are estimated differently for mothers and

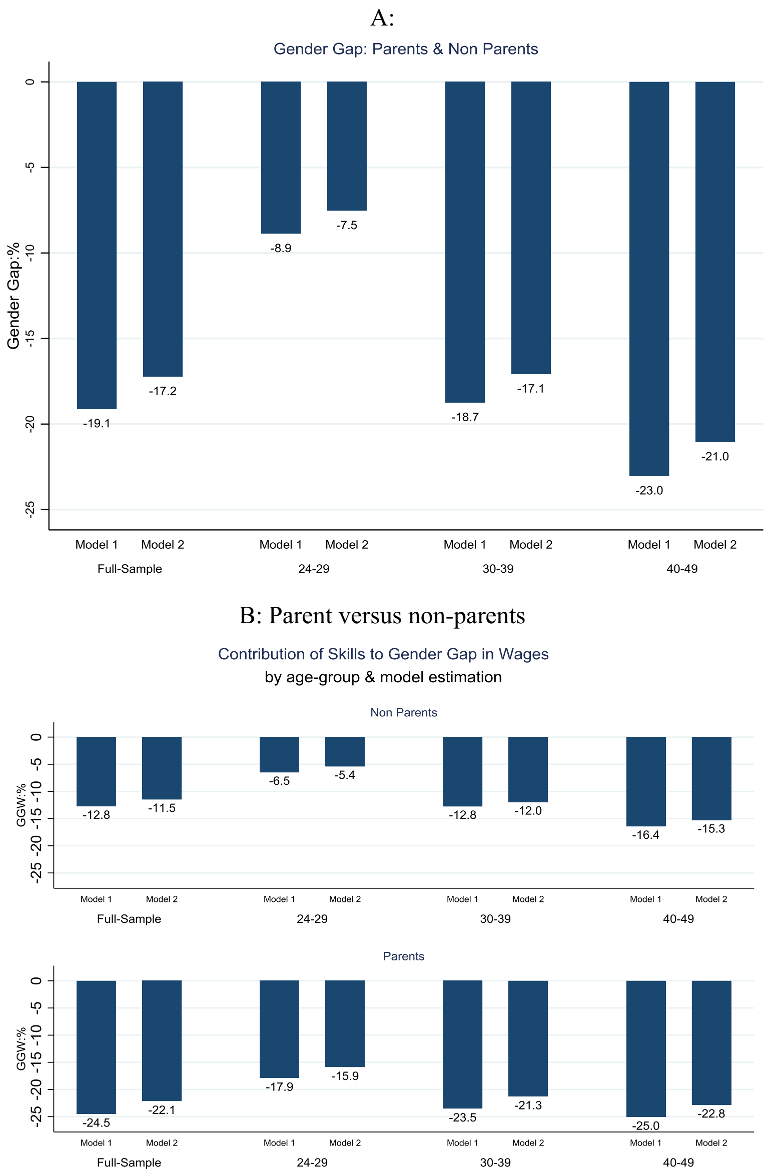

Fig. 3 Adjusted gender gaps in wages (women–men) by age and family type. These are adjusted gender gap in wages computed using coefficient estimates—marginal effects—from Tables 10 (full sample) and 11 (non-parent versus parents). For non-parents, the adjusted gender wage gap is the difference between the corresponding coefficient estimates for women without children minus coefficient estimates for males without children. For parents, the adjusted gender wage gap is the coefficient estimate for women with children since the reference group is men with children. Using model parameters estimates we compute the gender gap for individuals without children. We tested whether these differences in gender gaps are statistically different. The results from these test leads us to reject the null hypothesis of equality of gender gaps between these two models for all samples

Table 15 Wage equation (log hourly wages): gender gaps in wages and family: main results

	Full sample	By age cohort		
	24–49	24–29	30–39	40–49
	(1)	(2)	(3)	(4)
Model 1: baseline model				
Math scores	–	–	–	–
Reference men*children				
Men*no children	−0.117*** (0.01)	−0.0511* (0.03)	−0.0912*** (0.02)	−0.101*** (0.02)
Women*no children	−0.245*** (0.01)	−0.116*** (0.03)	−0.219*** (0.02)	−0.266*** (0.02)
Women*children	−0.245*** (0.01)	−0.179*** (0.03)	−0.235*** (0.02)	−0.250*** (0.01)
R2	0.417	0.376	0.415	0.459
Model 2: +math scores				
Math scores	0.0243*** (0.00)	0.0199*** (0.00)	0.0218*** (0.00)	0.0270*** (0.00)
Reference men*children				
Men*no children	−0.107*** (0.01)	−0.0581** (0.03)	−0.0817*** (0.02)	−0.0838*** (0.02)
Women*no children	−0.222*** (0.01)	−0.112*** (0.03)	−0.202*** (0.02)	−0.237*** (0.02)
Women*children	−0.221*** (0.01)	−0.159*** (0.03)	−0.213*** (0.02)	−0.228*** (0.01)
R2	0.443	0.386	0.436	0.488

Least squares regressions weighted by sampling weights and replication weights are used to compute jackknife standard errors (in brackets). Dependent variable: log gross hourly wage. Sample: employees aged 24–49. Numeracy scores are divided by 10. The constant term refers to "men with children." All specifications include country fixed effects and other individual characteristics such as age, experience, educational attainment level, and field of study. Detailed estimation results are upon request

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

non-mothers but excluding math scores—Higher panel of Table 15. Then, we add math scores to the wage equation and report the returns to math scores as well as the new gender wage gaps within the same math scores. We do so for all ages together (Column 1 of Table 15), as well as separately for the three age intervals. As before, for an easier visualization of all estimated gender wage gaps (parents and non-parents altogether, parents versus non-parents, and across and within math scores) Panel B of Fig. 3 displays all different gender wage gaps for parents and non-parents respectively (Table 15).

The first issue to highlight from the comparison of gender wage gaps between non parents and parents is that these gaps for parents are around twice as large as those for non-parents (12.8% for non-parents versus 24.5% for parents). Regarding the different age intervals, gender wage gaps are lowest for young non-parents, and increase not very substantially but steadily with age. Regarding parents, the pattern is similar, as gender wage gaps increase with age, but both the magnitude and the increase with age is bigger.

Second, the adjusted gender wage gap within the same math scores is somewhat smaller, particularly it drops for parents around 2.4 percentage points (or 9.7% in relative terms) and for non-parents around 1.3 percentage points (or 10% in relative terms). Nevertheless, adjusted wage gender gaps are still substantial. This means that to understand the underlying drivers of gender wage gaps, in addition to observed standard human capital variables and even precise measures of cognitive skills, such as math scores, other unobservable factors are taking place. This is particularly so for

Table 16 Two-step wage estimation: gender gaps in wages

	Full sample	By age cohort 24–49		
	24–49	24–29	30–39	40–49
	(1)	(2)	(3)	(4)
Model 1: basic human capital				
Math scores	–	–	–	–
Women	−0.319*** (0.01)	−0.082*** (0.02)	−0.323*** (0.02)	−0.359*** (0.01)
Athrho-ρ	1.315*** (0.04)	−0.093** (0.04)	1.111** (0.08)	1.309*** (0.07)
λ	0.43	−0.04	0.37	0.43
Model 2: +math scores				
Math scores	0.0231*** (0.00)	0.0198*** (0.00)	0.0220*** (0.00)	0.0256*** (0.00)
Women	−0.297*** (0.01)	−0.070*** (0.02)	−0.306*** (0.01)	−0.334*** (0.03)
Athrho-ρ	1.294*** (0.04)	−0.062** (0.04)	1.131*** (0.08)	1.260*** (0.08)
λ	0.42	−0.025	0.37	0.41
Sample	51,909	13,676	19,264	18,969

Least squares regressions weighted by sampling weights and replication weights are used to compute standard errors. Dependent variable: log gross hourly wage. Numeracy scores are divided by 10. Jackknife standard errors are in brackets. All specifications include country fixed effects and other individual characteristics such as age, experience, educational attainment, and field of study. Detailed results for the full sample are shown in Appendix Table 21. The parameter Athrho-ρ represents the inverse hyperbolic tangent of the correlation term between the unobservable of the selection equation and the wage equation and "ρ" the estimated correlation term between the unobservable of the selection equation and the wage equation. Data source: PIAAC

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

parents, where we find adjusted gender wage gaps between men and women with very similar human capital variables are still higher than 20%, primarily when we consider workers over 30 years.

4.6 Robustness checks—selection into the labor market and endogeneity of math skills

4.6.1 Selection into the labor market

We have addressed before that math skills are positively associated to entering the labor market, primarily for women. However, in the previous section we compute the association between math skills and wages only for the sample of workers, and thus do not take into account a potential female self-selection into the labor market.[28] If working women are not representative of all women as a result of differences in observed and unobserved factors, then the reported gender wage gap cannot be inferred for the whole population, as it would be biased. In particular, as it is very often the case, if working women are on average those with higher skills (as their opportunity cost of not working is higher), the estimates reported above would be downward bias. Hence, we need to address whether the results/patterns found in the previous section change when that selection is explicitly factored into the estimation.

[28] Basically, women who would have low wages may be unlikely to choose to work, and thus the sample of observed wages is biased upward.

To do this, we re-run the previous log wage estimations for all age groups together, but using a standard two-step Heckman approach. In the first stage, the probability of working is estimated, the Inverse Mills Ratio (IMR) (which computes (the inverse of) the probability of being in work) is obtained, and included as an additional covariate in the second-step wage regression. The main results can be seen in Table 13 (estimated gender gaps and returns to math skills as in previous tables). For identification, additionally to functional form, we have used, as usual, family variables, such as the presence of children in the household, leaving with a couple, the partner labor market status (1 = working), besides health status and first/second immigrant generation. Hence, our basic assumption is that these variables affect wages not directly but only through the participation decision.

The first issue to be noted is that the estimated correlation between the unobservables of the selection and the wage equation is positive and statistically significant for the full sample and for the age cohort above 24–29. This means that those unobservable factors that affect the probability of working are positively associated with those unobservables that affect wages for these workers. Typically, unobservables in wage equations are correlated with unobserved ability, and if we assume so, then the positive sign of this correlation term is easily understood. Secondly, when sample selection is considered in the estimation, gender wage gaps rise substantially but the main patterns remains: gender wage gaps are substantially smaller for young workers, math scores are positively associated with wages, and the gender wage gap within math scores decreases slightly when math scores are factored in.[29]

4.6.2 Endogeneity of math skills

Numerical skills may be endogenous for both labor market outcomes, as skills and labor market experience are likely to be causally related (see Hampf et al. 2017; Jimeno et al. 2016). Cognitive skills acquired in childhood are likely to affect future labor market paths: cognitive skills enable individuals to understand and perform better. Work experience may vary across similar individuals due to extended periods of unemployment or nonparticipation in the labor market, which, in turn, may affect cognitive skills. This productivity-enhancing effect of skills increases a person's wages (workers obtain better-paid jobs and have more stable labor market paths) or allows him or her to escape unemployment and find a job in the first place.[30]

In the presence of endogeneity, causal inference cannot be assessed unless valid instrumental variables are used. In the PIAAC sample, there are no obvious instruments that might be used for identification. As such, we prefer to acknowledge the potential endogeneity of cognitive skills for wages and present the empirical relation found between them and labor market outcome as an association between the two, and not as a causal predictor. This is the way we have dealt with it for the whole paper.

[29] For the sake of brevity, we do not include separate wage equations for parents and non-parents taking into account self selection, as the patterns remain very similar, both for non-parents and parents. The only difference, as seen in Table 13, is that gender wage gaps are higher, both for parents than for non-parents.

[30] The covariate *years of working experience* correlates with performance in the PIAAC mostly among less educated individuals (see Jimeno et al. 2016).

5 Summary and conclusions

The availability of more direct measures of cognitive skills for a cross-section of countries permits a deeper empirical research of the link between gender gaps in skills and gender gaps in labor market outcomes, in particular in the decision to work and in wages. To our knowledge, there are no prior empirical study which addresses this issue from an international perspective. In particular, we test whether there are gender gaps in cognitive abilities and seek to understand how those gaps are associated with some important labor market outcomes at different ages, which represent different stages along the life cycle, together with potential cohort effects. We focus on literacy and numeracy skills. To that end, we use data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), which offers unique information on skills at individual level together with standard labor market information such as wages, educational attainment, labor market experience, and type of job, making it a highly suitable data source for our purpose.

Individuals enter into the labor market with a particular level of cognitive skills but these levels may change upwards or downwards depending on the individual's particular labor path. Therefore, our analysis is performed by age groups (1) Entrants into the labor market (aged 24–29); (2) Prime age workers aged 30–39; (3) Prime age workers aged 40–49. Particular attention is paid to the age group that we denote as "entry age" (24–29 years) compared with the next age group (30–39), when motherhood plays an important role for women

Overall, our results confirm that gender gaps in literacy skills are insignificant. However, men exhibit consistently higher numeracy cognitive skills than women. On average, the gap amounts to 3.5–4.2%. Furthermore, it undergoes a substantial increase from 3.6 to 4.6% from age at entry into the labor market (24–29) up to age 30–39. For older ages, it decreases slightly. Additionally, gender gaps in math skills are particularly substantial for highly educated workers. We also assess whether gender gaps in math scores are different across fields of study. Our results confirm, perhaps unexpectedly, that gender gaps in numeracy skills are remarkable in absolutely all fields of study and for all ages. They range from 1.8% in health where women representation is high (reaching 70%), to 6.7% in social science, where women outstand men. If we restrict to men and women with university studies, we find remarkable gender gaps even in fields of study which require analytical competences, such as social science and science. These gaps also exist across all occupations and all countries. Finally, whereas differences in field of study and other labor market variables may be part of the factors underlying gender gaps in math skills, there is still a considerable fraction of it that remains even when we compare males and females that work in similar jobs and who chose the same field of study.

Second, adjusted gender gaps in labor market participation are very remarkable, around 18 percentage points, and increase with age. Additionally, math skills are positively associated with labor market participation, and differences in math skills are positively associated with gender gaps in labor market participation, primarily for young non-parents. For parents, although we find a positive association between math skills and labor force participation, its contribution to explain gender gaps in participation is limited, and other unobserved variables are likely to play a decisive role.

Finally, adjusted gender gaps in hourly wages are also remarkable and amount to 20% and rise substantially and steadily with age—from 8.8% at age entry, rise to 18% at the "maternity age" and rise again to 23% for 40–49 years. Furthermore, even when comparing men and women with similar individual skills and labor market characteristics average gender gaps amounts to 19%. By parenthood, gender wage gaps for parents are around twice as large as those for non-parents (13% for non-parents versus 24% for parents). Math skills are positively associated to wages, and more importantly, its contribution to explain gender wage gaps is around 1.9–2.5 percentage points (or between 10–15% in relative terms). Nevertheless, adjusted gender gaps tend to be significant even when maths skills are factor in the model and henceforth, there should other unobsevables-observables that play a more decisive role.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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6 Appendix

Table 17 Main sample characteristics used in lmp equation (24–49)

	Women Mean	Men Mean
Having at least a child	72.6%	59.7%
Having at least one child younger than 5 years old	29.9%	28.2%
Age	36.5	36.5
Leaving with a couple (1 = yes)	68.2%	64.8%
Partner-work (1 = yes)	61.4%	45.4%
First and second generation immigrant (1 = yes)	5.4%	5.7%
Good health (1 = yes)	73.0%	85.2%
Individual education		
Less than secondary	3.2%	2.9%
Secondary	46.0%	54.1%
Tertiary (not university)	19.4%	15.2%
University	31.5%	26.9%
Field of study		
General program	25.7%	26.6%
Humanities	18.0%	7.1%
Social science	19.7%	12.5%
Science	12.4%	40.3%
Agriculture	2.2%	3.8%
Health	21.0%	8.7%

Table 18 Main sample characteristics used in the wage equation

	Women	Men
Age	36.9	36.7
Individual education		
Primary	1.6%	2.7%
Secondary	42.5%	53.4%
Post-secondary (not university)	20.7%	15.9%
University	35.2%	28.0%
Field of study		
General program	21.4%	27.5%
Humanities	19.4%	13.3%
Social science	22.1%	42.5%
Science	12.7%	4.0%
Agriculture	2.2%	3.8%
Health	22.2%	8.9%
Labor market experience (years)	17.4	18.9
Tenure	7.9	8.6
Occupations		
Technicians and associated professionals	10.3%	17.2%
Service workers and shop and market sellers	48.7%	42.9%
Skilled agricultural and fishery workers	14.8%	6.4%
Craft and related trades workers	22.5%	11.4%
Plant and machine operators and assemblers	1.0%	3.2%
Elementary occupations	2.7%	18.9%
Large firm	14%	17%
Part-time	17%	5%
Private firm	75%	85%
Fixed-term contract	39%	38%

Occupational classification of respondent's job at 1-digit level (ISCO 2008)

Table 19 Labor market participation equation: gender gaps in labor market participation (detailed results)

	(1)	(2)	(3)
Math scores		0.0424*** (0.00)	0.0396*** (0.00)
Women	−0.774*** (0.02)	−0.731*** (0.02)	−0.727*** (0.03)
Children (1 = yes)	−0.0459 (0.04)	−0.0369 (0.04)	−0.0321 (0.04)
Children <5 years old (1 = yes)	−0.335*** (0.03)	−0.338*** (0.03)	−0.341*** (0.03)
Having a couple (1 = yes)	0.118*** (0.04)	0.105** (0.04)	0.101** (0.04)
Partner-work (1 = yes)	−0.0428 (0.03)	−0.0658* (0.03)	−0.0661* (0.03)
Bad-health (1 = yes)	−0.183*** (0.03)	−0.162*** (0.03)	−0.159*** (0.03)
First/second generation immigrant (1 = yes)	−0.238*** (0.05)	−0.177*** (0.05)	−0.189*** (0.05)
Age	0.0127*** (0.00)	0.0139*** (0.00)	0.0145*** (0.00)
Education (ref: primary)			
Secondary	0.650*** (0.05)	0.487*** (0.05)	0.411*** (0.05)
Post-compulsory secondary	0.862*** (0.05)	0.615*** (0.05)	0.459*** (0.06)
University	1.095*** (0.05)	0.762*** (0.06)	0.615*** (0.07)
Field of study (ref: general program)			
Humanities			0.0660 (0.04)
Social science			0.294*** (0.04)
Science			0.183*** (0.03)
Agriculture			0.249*** (0.07)
Health			0.232*** (0.04)
Constant	0.955*** (0.09)	−0.0996 (0.12)	−0.0807 (0.12)
Observations	63,830	63,830	63,830

Jackknife standard errors in parentheses; all estimations include country fixed effects. Estimation method used the survey structure of the PIAAC database

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 20 Wage equation (log hourly wages): gender gaps in wages—detailed results

	(1)	(2)	(3)	(4)	(5)
Math scores	–	0.0255*** (0.00)	–	0.0246*** (0.00)	0.0178*** (0.00)
Women	−0.206*** (0.01)	−0.177*** (0.01)	−0.191*** (0.01)	−0.172*** (0.01)	−0.177*** (0.01)
Age	−0.00122 (0.00)	−2.60e−05 (0.00)	−0.000785 (0.00)	0.000302 (0.00)	0.000813 (0.00)
Education (ref: primary)					
Secondary	0.202*** (0.03)	0.103*** (0.03)	0.158*** (0.03)	0.0770** (0.03)	0.0584* (0.03)
Post-compulsory secondary	0.383*** (0.03)	0.233*** (0.03)	0.310*** (0.03)	0.188*** (0.03)	0.109*** (0.03)
University	0.667*** (0.03)	0.461*** (0.03)	0.590*** (0.03)	0.417*** (0.03)	0.269*** (0.03)
	0.0179*** (0.00)	0.0172*** (0.00)	0.0176*** (0.00)	0.0170*** (0.00)	0.00843*** (0.00)
Field of study (ref: general program)					
Humanities			0.0360** (0.02)	0.0216 (0.02)	0.0110 (0.02)
Social science			0.0995*** (0.01)	0.0709*** (0.01)	0.0547*** (0.01)
Science			0.106*** (0.01)	0.0641*** (0.01)	0.0294** (0.01)
Agriculture			0.00678 (0.03)	−0.0043 (0.03)	0.0019 (0.03)
Health			0.0649*** (0.01)	0.0613*** (0.01)	0.0386*** (0.01)
Occupations (ref. category : professionals, technicians and associated professionals)					
Clerks					0.237*** (0.01)
Service workers and shop and market sellers					0.0671*** (0.01)
Craft and related trades workers					−0.0150 (0.01)
Plant and machine operators and assemblers					−0.121*** (0.04)
Elementary occupations					0.0449*** (0.01)
Large firm					0.121*** (0.01)
Part-time					0.119*** (0.02)
Fixed-term contract					−0.0930*** (0.01)
Tenure (years)					0.0101*** (0.00)
Constant	2.518*** (0.04)	1.851*** (0.04)	2.490*** (0.04)	1.856*** (0.04)	1.999*** (0.04)
Observations	41,138	41,137	41,138	41,137	41,137
R-squared	0.407	0.436	0.412	0.438	0.499

Jackknife standard errors in parentheses; all estimations include country fixed effects. Estimation method used the survey structure of the PIAAC database

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 21 Heckman selection model: wage equation (log hourly wages): gender gaps in wages—detailed results

	Model 1: baseline		Model 2: baseline + math scores	
	Wage equation	Selection equation	Wage quation	Selection quation
Math scores			0.0231*** (0.00)	
Women	−0.319*** (0.01)	−0.709*** (0.03)	−0.298*** (0.01)	−0.710*** (0.03)
Age	0.00185** (0.00)	0.0150*** (0.00)	0.00263*** (0.00)	0.0141*** (0.00)
Education (ref: primary)				
Secondary	0.301*** (0.03)	0.578*** (0.06)	0.220*** (0.03)	0.569*** (0.06)
Post-compulsory secondary	0.471*** (0.03)	0.729*** (0.07)	0.352*** (0.03)	0.708*** (0.07)
University	0.779*** (0.03)	0.951*** (0.07)	0.612*** (0.03)	0.934*** (0.07)
Field of study (ref: general program)				
Humanities	0.0564*** (0.02)	0.0877** (0.04)	0.0414** (0.02)	0.0968** (0.04)
Social science	0.160*** (0.01)	0.352*** (0.04)	0.131*** (0.01)	0.351*** (0.04)
Science	0.154*** (0.01)	0.240*** (0.03)	0.113*** (0.01)	0.241*** (0.03)
Agriculture	0.0503* (0.03)	0.186*** (0.07)	0.0388 (0.03)	0.178** (0.07)
Health	0.114*** (0.02)	0.228*** (0.04)	0.109*** (0.01)	0.232*** (0.04)
Labor market experience	0.0164*** (0.00)		0.0161*** (0.00)	
Children (1 = yes)		−0.0009 (0.03)		0.00170 (0.03)
Children younger than 5 years old (1 = yes)		−0.321*** (0.03)		−0.332*** (0.03)
Leave with a couple		0.00577 (0.03)		0.00913 (0.03)
Partner-work (1 = yes)		−0.0399 (0.03)		−0.0209 (0.03)
Bad-health (1 = yes)		−0.0692*** (0.03)		−0.0804*** (0.03)
First/second generation immigrant (1 = yes)		−0.189*** (0.04)		
Constant	2.235*** (0.04)	0.346*** (0.09)	1.648*** (0.05)	0.372*** (0.10)
athrho	1.315*** (0.04)		1.294*** (0.04)	
Ln(σ)	−0.694*** (0.01)		−0.719*** (0.01)	

Jackknife standard errors in parentheses; all estimations include country fixed effects. Estimation method used the survey structure of the PIAAC database. The parameter "athrho" represents the inverse hyperbolic tangent of the correlation term between the unobservable of the selection equation and the wage equation. Ln(σ) Is the log of the standard error of the residual in the wage equation

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

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