The role of literacy and numeracy skills across gender and countries

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Abstract

New data availability on skills has opened the possibility to answer different research questions that were difficult to tackle before. The recent work of Hanushek et al. (2015) using the PIAAC survey of adult skills has shown that returns to skills are heterogeneous for different countries. Most of the research has used only one skill type (often literacy or numeracy) to generalize the impact of skills. This article aims to disentangle the differences of numeracy and literacy skills and its interaction effect on labor market outcomes in a context of technological change. By including education in the analysis, I am also able to compare the impact of numeracy and literacy skills to education. The article focuses on the different impact of numeracy and literacy skills for labour market outcomes targeting particularly gender differences. Overall, results show that nowadays, numeracy and literacy skills matter significantly for men and women. However, numeracy pays off more than literacy skills. Numeracy and literacy seem not to be complementary, except among female non-graduates. And skill differences do not explain gender wage gap. Women receive always a wage penalty, even among homogeneous skill groups such as STEM graduates.

Keywords: Skills and Human Capital, Labour productivity, Gender Wage Differentials, Labour Force Composition
JEL-Classification: I26, J16, J24, J31, J82

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1 Introduction

The causal relationship between education and earnings is usually explained through two channels. On the one hand, the human capital theory explains that, in perfect competitive markets, education increases the individual marginal productivity and thus leads to higher earnings (Schultz 1961; Becker 1962). On the other hand, the contract or signalling theory argues that workers use educational credentials to signal their abilities to the employers. Employers believe that these credentials are positively correlated to higher abilities which will make employees more productive and therefore justify higher earnings (Spence 2002).[1]

Quantitative measures of skill level allow better identification of individual productivity, and to disentangle the impact of schooling attainment and cognitive abilities for labour market outcomes. Cognitive skill measures and cognitive tests usually try to estimate the capacity of reasoning and solve problems. There are established measures of skills that account for different competences.[2] The ones that are used most are literacy (which usually measures reading comprehension and writing skills) and numerical skills. Despite a large body of literature that investigates returns to cognitive skills, most of the studies only use one skill measure and try to explain labour outcomes by this single indicator (Hause 1972; Bishop 1992; De Baldini Rocha and Ponczek 2011). They have either replaced education by skills or added skills as explanation for wages (Blackburn and Neumark 1995; Murnane, Willett and Levy 1995). Only very few included both skill measures, but they failed to determine their joint effect, measured by the interaction of numeracy and literacy skills (Taubman and Wales 1974; Willis and Rosen 1979; McIntosh and Vignoles 2001; Shomos 2010). Many agree on the positive impact of personal skills for labour outcomes (Bronars and Oettinger 2006; Cameron and Heckman 1998; Green and Riddell 2003). However, the evidence about the economic returns to numeracy and literacy skills is far from conclusive (Bound, Griliches and Hall 1986). Being able to use and manipulate both words and numbers has become essential in the current society, but the joint effect of numeracy and literacy skills, as well as their independent and relative importance are not yet clear.

Hanushek et al. (2015) have been pioneers in using the survey of adult skills. This survey is part of the Programme for the International Assessment of Adult Competencies (PIAAC), an international adults survey that provides standard background information as well as comparable skill measures of cognitive and workplace skills, to analyse the role of skills across countries. This dataset is the same I use in my analysis. The main finding of their study documents that wage impacts of skills are heterogeneous and vary significantly by country. Although they show that their results do not depend on the choice of a particular skill measure, Hanushek et al. (2015) focus only on numeracy as measure of skills. This contrast to my study because their focus is neither to analyse the relationship between numeracy and literacy skills nor their interaction effect for wage determination.

Fewer studies have analysed the differences between economic returns to numeracy and literacy across gender, particularly with regard to differences in skill importance to labour productivity. Bound, Griliches and Hall (1986) is one of the pioneer studies that looks explicitly at the differences of schooling returns between men and women. Using IQ scores as proxy for abilities, they found that the IQ-schooling-wage relationship is essentially sex-blind. However, due to data limitations, they

1. Cognitive abilities can be determined by innate circumstances before birth, but also they can be acquired and developed in the life course (Cunha and Heckman 2007).

2. For example, the Cognitive Abilities Test (CogAT) tries to assess student's abilities in reasoning and problem solving using verbal, quantitative, and non-verbal (spatial) symbols.

were unable to determine if ability is priced differently in the marketplace for men and women. Two gaps can be identified in the gender related literature. First, most of the studies that examine the relationship between gender differences and cognitive skills analyse the effect of gender differences on skill acquisition, rather than the impact of those skills on labour market outcomes (Lindberg et al. 2010; Niederle and Vesterlund 2010). Second, from the few studies that investigate the economic returns to skills, most of them concentrated on analysing the returns to numeracy skills than on literacy skills and even fewer on studying the effect of the interaction between numeracy and literacy across gender. This is probably because numeracy test scores have been largely confirmed to be a good predictor for schooling decisions and future income (Paglin and Rufolo 1990; Murnane, Willett and Levy 1995; Grogger and Eide 1995; Murnane, Willett and Levy 1995; Altonji and Blank 1999).[3]

This study has two main objectives. First, it aims to disentangle the differences of numeracy and literacy skills and its interaction effect on labour market outcomes in a context of technological change. By including education in the analysis, I will also be able to compare the impact of numeracy and literacy skills to education. Second, by studying groups with homogeneous skill distribution, the paper seeks to determine whether numeracy and literacy skills matter significantly for men and women. It will also examine if women are penalized in the labour market among groups of adults that have potentially the same skills, such as those who study Science, Technology, Engineering and Math (STEM) graduate programs.

The main goal of this research is to provide a descriptive overview of the impact of skills on earnings, rather than analysing their causal effect. In this article, I present a simple theoretical framework that uses wages as measure of individual productivity, and literacy, numeracy and education as the main explanatory variables. This framework enlightens the interpretation of the various parameters of interest when not controlling by unobserved skills and other factors in the main specifications. It shows that the estimated coefficients are compound measures of unobserved and observed factors. Hereby, I will talk about “returns” to skills to refer to non-causal estimates, as it has also been done in the literature.

Across different model specifications and cross-checks, five main results are confirmed in this paper: First, numeracy and literacy skills matter for wages. Numeracy though, have larger point estimates than literacy skills. Second, there is little complementarity between numeracy and literacy skills, except among female non-graduates. Third, non-linearity effects of skills seem to be present, but I found no clear pattern. Fourth, skill differences do not explain the gender wage gap. Thus, women are penalized in the labour market, even when having similar skills distribution than men. Fifth, country-specific and quantile income analyses show that the role of skills is very heterogeneous across countries.

The study is carried out as follows. First, I analyse the overall impact of skills across countries and quantile income groups, and then study the role of skills for each country. Section 2 provides a literature review. Section 3 develops a theoretical framework to clarify the estimation strategy. Section 4 describes the PIAAC data, details the groups of analysis and presents descriptive statistics of skills and labour market outcomes. Section 5 details the empirical strategy, the main results and robustness checks. Section 6 interprets and discusses the results; and section 7 concludes. Variable descriptions and estimations results different from the basic models are included in the Appendix.

3. Few exceptions look at the role of literacy and earnings such as Green and Riddell (2003).

2 Literature review

The literature establishes that educational attainment and wages are well predicted by cognitive skills. Cawley, Heckman and Vytlacil (2001) added that the impact of cognitive ability on wages, controlling for education, is small and varies by race and gender. The impact of cognitive skills is usually decomposed into different measures: achievement tests that aim to capture the rate at which people learn, and IQ tests such as the Raven's progressive matrices to capture acquired knowledge (Kautz et al. 2014). Further, these tests are influenced by effort and noncognitive skills (Heckman, Stixrud and Urzua 2006).[4]

To measure the impact of cognitive skills, empirical studies have either replaced education by skill measures or added skills as explanation for wages. Blackburn and Neumark (1995) is one of the pioneer studies that includes test scores as proxy for individual abilities on wage regressions. They tried to assess endogeneity in test averages and schooling, adding a set of instruments, such as parental educational background, age of siblings, etc. Most of such studies have employed a single, generic measure of skills. Hause (1972) and Willis and Rosen (1979) examined the role of quantitative measures on earnings and found that they significantly affect earnings of high school and college graduates, but they did not include literacy skill measures. On the other hand, De Baldini Rocha and Ponczek (2011) examined the effects of adult literacy on individuals' income and employability in Brazil using the PME monthly employment survey. They found that literacy increased wages by 4.4% points and the probability to be employed by 4.3% points. In this case, numeracy was not included in the analysis.

The study of the combined effects of numerical and verbal skills started only relatively recently. For instance, McIntosh and Vignoles (2001) investigated the influence of mathematical and verbal skills on wages for the UK, and found that literacy and numeracy skills are positively associated with earnings. They tackled selection bias by estimating first the impact of skills into employment. Dougherty (2003) investigated the non-linear effects of numeracy and literacy on college attainment and hourly earnings. They found statistically significant non-linear effects of numeracy. However, no evidence of non-linear effects of literacy were found.

Most of these studies have been carried out using national survey data such as the National Longitudinal Survey of Youth (NLSY) (Dougherty 2003), the Project Talent data (US) (Hause 1972), the NBER-Thorndike-Hagen survey (Willis and Rosen 1979), or the OECD Survey of adult skills (PIAAC) on Australian population (Shomos 2010; Shomos and Forbes 2014). The two latter studies analysed the contribution of literacy and numeracy to schooling, employment and earnings using the Australian PIAAC data. They found a high correlation between numeracy and literacy test scores for Australian data and highlight the strong links between numeracy and literacy skills, as well as between employment and wages. However, they did not differentiate between returns to each skill in their estimation analysis. Other cross-country data like the Programme for International Student Assessment (PISA) has been used to measure school students' achievements. Hanushek et al. (2015) has been the pioneer in using PIAAC data and measuring returns to skills across countries.

Gender differences are particularly important when studying the effects of skills in labour market

4. Although innate abilities are usually associated to those who are "in the genes", from a psychological perspective, it is important to differentiate them from those which are inherited.

outcomes. After investigating extensively the gender differences in numerical performance and verbal ability, psychologists have gathered solid evidence that no substantial differences exist in verbal and mathematical abilities between gender (Else-Quest, Hyde and Linn 2010; J. S. Hyde and M. C Linn 1988; Lindberg et al. 2010). Economists, have recently studied the relationship between cognitive skills and gender differences. Niederle and Vesterlund (2010) for example, argue that the reported test scores do not necessarily reflect the gender differences in math skills, but instead the gender gap in mathematics performance might be explained partly by the differential manner in which men and women respond to competitive test-tasking environments.

Although we know more about the drivers of potential differences or similarities between men and women on test scores, little research has looked at the impact of different skills on earnings across gender. One of the few exceptions is the study of Lindley (2012), who found that women lost out from technological change between 1997 and 2006, despite the large increase in educational attainment. This finding was explained by their low level of numeracy, literacy and other skills required to perform tasks that are correlated with technical change such as computerization. Also, Almenberg and Dreber (2015) found that women participate less than men in the stock market and score lower on financial literacy.[5] The aim of this paper is to contribute to the existing literature by studying the impact of different skills such as numeracy and literacy on labour market outcomes for men and women. By using the new PIAAC data, this article also intends to give insights into the independent and joint effects of numeracy and literacy skills on earnings across different countries and for groups at different income quantiles, and with different level of education.

3 Basic framework

Variables such as skills and schooling are central for determining labour market outcomes. However, it is very difficult to disentangle the causal effect of those variables in absence of experimental variation. The framework developed here is intended to guide the correct interpretation of the estimations carried out in Section 5. Although this framework does not attempt to estimate causal relationships, I address here two main econometric concerns.

First, one may worry about reverse causality. While it is plausible to assume that education can be pre-determined at labour market entry, it is harder to make a similar assumption for skills which are measured contemporaneously with labour market outcomes. Using measures of skills for workers in the labour force has many advantages, but it is indeed less likely that cognitive skills measured after labour market entry are not affected by job specific experience and training. To address this problem, this model assumes that the contemporaneous measures of experience capture the fact that skills are learnt over time.

Second, it is natural to think about the potential bias driven by omitted variables. While measures of numeracy and literacy skills help explaining wages, it is also very likely that other cognitive and

5. Other disciplines have also looked at the relationship between numeracy and literacy skills. For instance, Telford et al. (2012) found strong evidence for positive relationships between literacy and numeracy scores at the school level, and cardioid-respiratory fitness. Carreiras et al. (2015) found different biochemical pathways for literacy and numeracy. Specifically, they detected brain activation differences for literacy and numeracy from early stages of processing in the temporal-occipital and temporal-parietal regions.

non-cognitve skills, which are unobserved in the PIAAC data, might also matter significantly for earnings. One may wonder how the omission of other wage determinants affects OLS estimates of numeracy and literacy. The following framework allows to investigate the sign and magnitude of this potential bias.

As starting point, let us assume a perfect competitive market where wages are determined by the individual worker's productivity. In this context, firm profit maximization of inputs will lead to equate the wage to the marginal product of labour. Equation 1 summarizes individual productivity as follows:

$$w_i = f(l_i, n_i, edu_i, o_i, exp_i, \chi_i) \tag{1}$$

where w_i refers to log wages for worker i, l_i and n_i refer to general functions of literacy and numeracy skills respectively, edu_i to years of education, o_i to all unobservables (which include individual cognitive and non-cognitive skills other than numeracy and literacy), exp_i to experience, and χ_i to all other control variables.[6]

To keep the framework very simple, let us assume a linear relationship between wages, skills and exogenous variables. Although the relationship between wages and experience is modelled in the empirical equation as a polynomial of second degree, and the empirical framework also includes the interaction $num * lit$, for simplicity equation 2 is presented here in its linear form:

$$w_i = \alpha_0 + \alpha_1\ n_i + \alpha_2\ l_i + \alpha_3\ o_i + \alpha_4\ edu_i + \alpha_5\ exp_i + \alpha_6\ \chi_i + \epsilon_i \tag{2}$$

where $n_i, l_i, o_i, edu_i, exp_i$ and χ_i refer to the variables detailed before in equation 1, and additionally α_0 refers to the intercept, α_1 to α_6 to the coefficient estimates of the relevant variables, and ϵ_i to the error term of this wage equation.

Since skills are not determined exogenously, literacy, numeracy and unobservable skills are modelled in a very general and flexible way. The following equations 3, 4, and 5 show that numeracy, literacy and unobservables depend, in fact, of all other variables included in the analysis.

As mentioned before, skills are determined by the level of experience. Also it is very likely that they depend on the level of education and personal characteristics. Equations 3 to 4 make also explicit the potential dependency of numeracy and literacy skills on unobservables (o_i). Likewise, one can well think that having good comprehension skills can help to score higher in numerical problems, and vice-versa. For this reason, the model allows for the interdependence of numeracy on literacy skills. Finally, equation 5 shows that both numeracy and literacy skills can affect achieving other unobservable skill characteristics.

Hence, under the linearity assumption, numeracy, literacy and unobservables can be summarized as follows:

$$\begin{aligned} l_i &= \beta_0^l + \beta_1^l\ n_i + \beta_2^l\ o_i + \beta_3^l\ edu_i + \beta_4^l\ exp_i + \beta_5^l\ \chi_i + \mu_i^l & (3) \\ n_i &= \beta_0^n + \beta_1^n\ l_i + \beta_2^n\ o_i + \beta_3^n\ edu_i + \beta_4^n\ exp_i + \beta_5^n\ \chi_i + \mu_i^n & (4) \\ o_i &= \beta_0^o + \beta_1^o\ n_i + \beta_2^o\ l_i + \beta_3^o\ edu_i + \beta_4^o\ exp_i + \beta_5^o\ \chi_i + \mu_i^o & (5) \end{aligned}$$

6. Unobservable skills which include cognitive and non-cognitive skills different from numeracy and literacy can be innate or learnt. In the empirical exercise, the set of control variables includes experience (exp_i) and experience squared (exp_i^2), industry and occupational dummies, civil status, number of children, employment status of the partner, etc.

where μ_i refers to the error term of each respective equation. After substituting equation 5 into equation 2 and grouping by independent variables, one obtains the following reduced form of the wage equation:

$$\begin{aligned} w_i = \quad & \alpha_0 + [\alpha_1 + \alpha_3\beta_1^o]\ n_i + [\alpha_2 + \alpha_3\beta_2^o]\ l_i + [\alpha_4 + \alpha_3\beta_3^o]\ edu_i + [\alpha_5 + \alpha_3\beta_4^o]\ exp_i + \\ & [\alpha_6 + \alpha_3\beta_5^o]\ \chi_i + [\epsilon_i + \alpha_3\mu_i^o] \end{aligned} \tag{6}$$

where the estimated parameters of n_i, l_i, edu_i, exp_i, and χ_i are summarized by:

$$\varphi_1 = \alpha_1 + \alpha_3\beta_1^o \tag{7a}$$
$$\varphi_2 = \alpha_2 + \alpha_3\beta_2^o \tag{7b}$$
$$\varphi_3 = \alpha_4 + \alpha_3\beta_3^o \tag{7c}$$
$$\varphi_4 = \alpha_5 + \alpha_3\beta_4^o \tag{7d}$$
$$\varphi_5 = \alpha_6 + \alpha_3\beta_5^o \tag{7e}$$
$$\zeta_i = \epsilon_i + \alpha_3\mu_i^o \tag{7f}$$

Certainly, without controlling for unobservables, the estimates of equation 6 will reflect the compound effects of different factors that determine skill acquisition and schooling investments. For simplicity, here I will focus only on numeracy estimates (φ_1). Similar reasoning applies to other estimates. Equation 7a shows that:

- When the effect of unobservables on wages is zero ($\alpha_3 = 0$), then the OLS estimate of numeracy is identified by the direct effect of numeracy on wages ($\varphi_1 = \alpha_1$).
- However, when unobservables are correlated with wages ($\alpha_3 \neq 0$) and also correlated with other observed regressors such numeracy ($\beta_1^o \neq 0$), the numeracy OLS estimate (φ_1) will be biased. The size of the bias will be given by the interaction of the direct and indirect effect of other unobservable skills ($\alpha_3\beta_1^o$).

In equation 6, the error term will be bigger due to unobservables. As shown in equation 7f, ζ_i comprises ϵ_i from equation 2 and μ_i^o from equation 5. The interpretation of estimated coefficients is now straightforward. The estimated φ_1 captures the direct effect of numeracy (α_1) and the direct and indirect effect of unobservable skills on wages ($\alpha_3\beta_1^o$), where α_3 can be interpreted as the impact of unobservables on wages, and β_1^0 as the impact of unobservables on numeracy skills.

To investigate the direction of the bias, three possible scenarios are described below and summarized in Table 1.

Case 1: $\alpha_3 < 0, \beta_1^o > 0$ This case refers to the context in which unobservable skills correlate negatively with wages ($\alpha_3 < 0$) and positively with numeracy skills ($\beta_1^o > 0$). This case could be attributed to very creative people who may be very good at performing numerical computations, but at the same time they are egocentric. This particular behaviour turns to be noxious for achieving higher wages. However, it is hard to think about this type of skills.

Case 2: $\alpha_3 > 0, \beta_1^o > 0$; or $\alpha_3 < 0, \beta_1^o < 0$ In these cases, unobservable skills are either positively or negatively correlated with numeracy and wages. Both scenarios will bias upward the OLS estimates.

Table 1: Four cases depending on the sign of $\alpha_3\beta^o$

	$\beta^o > 0$	$\beta^0 < 0$
$\alpha_3 < 0$	Case 1 downward bias	Case 2 upward bias
$\alpha_3 > 0$	Case 2 upward bias	Case 3 downward bias

Where α_3 and β^0 represent the direct and indirect effect of all other unobservable variables on wages, respectively.

In other words, the OLS estimates ($\hat{\varphi_1}$) will be higher than the true estimates ($\hat{\alpha_1}$) obtained if we could observe the effect of unobservable skills.

The scenario under which unobservable skills (o_i) are positively correlated with wages ($\alpha_3 > 0$) and with numeracy skills ($\beta_1^o > 0$), is the most plausible one. In terms of the Big Five Personality Factors, it is intuitive to think that personal characteristics like openness and conscientiousness will impact positively on cognitive skills such as numeracy as well as on wages.[7] It might well also be the case that unobservable skills correlate negatively with wages and numeracy skills. For example, the presence of extreme neuroticism or anxiety can make people very anxious to the point that it does not allow employees to work and therefore reduces wages directly. At the same time, this anxiety does not allow them to concentrate, leading to a decrease in their numeracy and literacy performance. Although the latter case will be qualitatively different from the former, in both cases the sign of the bias will be positive.

To investigate the magnitude of this bias let us assume that literacy was not observed and that omitting literacy produced similar bias than any other unobservable variable. In this case the estimated equation is identical to equation 6, but it does not include literacy in the regressors. After comparing the estimates of the model presented in equation 6 with the one that does not include literacy as regressor, results confirm that estimates with omitted literacy are biased upward. Furthermore, the effect of the bias is in the range between 5.6% to 6.9%.

Case 3: $\alpha_3 > 0, \beta_1^o < 0$ In this case, unobservable skills are indirectly negatively correlated with numeracy, but positively correlated with wages. To illustrate the link between unobservable skills and numeracy, I present here a brief review of what the literature says respect to the relationship between non cognitive and cognitive skills.[8] Numeracy will be taken as proxy for cognitive skills, and unobservables as proxy for non cognitive skills. In general, the literature agrees on a strong relationship between personality factors and specific cognitive abilities.[9] For instance, the literature explains the negative impact of unobservable on wages ($\alpha_3 > 0$) by finding that openness and extraversion predict lower order of cognitive abilities, particularly for young adults (Baker and Bichsel 2006; Graham and

7. The Big Five Personality Factors or usually called "Big Five" are commonly used by psychologists to generalized personality traits into Openness to experience, conscientiousness, Extraversion, Agreeableness, and Neurotiscim.

8. Heckman and Kautz (2014) show that personality traits predict labour outcomes. Some evidence, particularly from the field of Gerontology, shows that some of the Big Five and cognitive skills are strongly associated between them.

9. In psychology, most studies on personality predictors have been mainly fluid ability (Gf) and crystallized ability (Gc). "Gf refers to the ability to reason and solve new problems independently of previous acquired knowledge" (Jaeggi et al. 2008, p.1), and it is critical for various cognitive tasks. On the other hand, "Gc captures the influence of learning, education, in different domains" (Schipolowski, Schroeders and Wilhelm 2014, p.2).

Lachman 2012). In the same way, one might well think that $\beta_1^o < 0$ is plausible when other factors such as conscientiousness (“the tendency to be organized, responsible, and hard-working” (Heckman and Kautz 2014, p.4)), agreeableness (“the tendency to act in a cooperative, unselfish manner”(Heckman and Kautz 2014, p.4)) can positively matter for wages. Then, if the overall causal relationship between traits and cognitive skills is positive, the OLS estimates will be biased downward. As a result, we will obtain lower bound estimates of the real effect of skills on wages.

4 Data

This study uses the Survey of Adult Skills which is part of the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the Organization for Economic Co-operation and Development (OECD). PIAAC is an international survey that assembles standard background information as well as comparable skill measures of cognitive and workplace skills.
In this survey, 166 000 adults aged between 16 and 65 years were interviewed, who represent the entire population of adults living in households in 24 countries.

The first round of PIAAC was collected between August 2011 to March 2012 in most participating countries, and it includes Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation (Moscow), Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States. PIAAC has been designed to be valid cross-culturally and cross-nationally. Participating countries were requested to adapt the questionnaires to nation-specific circumstances in domains such as educational attainment and participation, labour-force participation and employment. The analysis presented here includes all the countries for which public information was freely available.[10]

The background questionnaire collected information in five different areas: basic demographic and background characteristics, educational attainment and participation, labour-force status and employment, and social outcomes. The final section focused on literacy and numeracy practices as well as the use of skills.

The main skills assessed by PIAAC are numeracy, literacy and technology-related problem solving measures. Skills are defined as follows: Literacy is defined as “the ability to understand, evaluate, use and engage with written texts in different contexts in order to participate in society, achieve goals, develop knowledge and fulfill personal aspirations” (OECD 2012, p.20). Numeracy consists in “the ability to access, use, interpret and communicate mathematical information and ideas in an period where managing mathematical content and processing quantitative information and ideas is crucial for daily life” (OECD 2012, p.34).

Proficiency scores for each skill range from 0 to 500 points. Levels are ranked from low to high proficiency, respectively (OECD 2013b). PIAAC data includes 10 different plausible values (PVs) of literacy, numeracy and problem solving in technology-rich environment. PVs are estimated proficiency scores of each individual. More precisely, each PV replicates a probable score distribution

10. The study excludes the Russian Federation, since information on Moscow is not representative for all the country. This restriction has been also made by Hanushek et al. (2015).

that summarizes how well each respondent answered a small subset of the assessment items; and, how well other respondents from a similar background performed on the rest of the assessment item pool (PIAAC 2015).[11] PVs are strongly correlated across skills for each individual, which confirms the stability of proficiency scores. Results of this paper employ only one PV for each skill. Basic model results are tested by comparing the analysis using other PVs.

4.1 Descriptive statistics of the data

In this research, I am interested in studying the effect of skills on earnings, conditional and unconditional on level of education. One objective of the analysis is to determine the mean impact of cognitive skills on earnings and to compare the magnitude of this effect with schooling returns. In other words, to determine how much a change in skill scores and level of education will impact on mean wages of men and women. However, the effect of skills might vary substantially across groups with different levels of education. For this reason, the study will also investigate the effect of skills for different groups conditional on their educational level.

Furthermore, the impact to literacy and numeracy skills may vary for graduates from different fields of study. Dougherty (2003) pointed out that numeracy has higher impact on earnings mostly through its effects on college attainment, but also directly. Indeed, the decision to go to college or to study a particular graduate program is not random and it can well be the case that the decision to invest more in education is influenced by higher earnings. Within educational programs such as Science, Technology, Engineering and Math (STEM) and Non-STEM, graduates have similar skill scores.[12]

Therefore, the analysis of skill scores and their impact for labour market outcomes is carried out first using the total sample (including education as an additional regressor), and separately for other population groups. The main groups of analysis are as follows:

- **TOTAL**: all adults between 16 and 65 years working full-time (at least 30h per week). Cross-checks used also workers with at least 15h of work per week.[13]
- **GRADUATES**: adults with tertiary-professional degree or more (minimum level of education ISCED4A-B-C).[14]
- **Non-GRADUATES**: all adults without higher education i.e. tertiary-professional degree or more (maximum level of education ISCED 3A-B, C long).
- **STEM**: graduates completed educational programs such as science, mathematics, computing, engineering, and educational research.

11. They are computed at the population level, but cannot be used to estimate an individual's proficiency because the uncertainty in the latent proficiency measure.

12. List of STEM disciplines varies by organization. I took as reference of STEM-eligible degrees, the one provided by the US immigration office.

13. Hirsch (2005) showed that part-time workers receive considerably lower hourly earnings than do full-time workers mainly due to the role of worker-specific and occupational skill requirements. Since lack of this type of specific skills characteristics in the data and to avoid endogeneity issues risen from different preferences to work part-time or full-time, part-time workers with less than 15h per week have been excluded from the analysis.

14. ISCED refers to the International Standard Classification of Education divided in 7 categories: 1 - primary or less (ISCED 1 or less, 2 - lower secondary (ISCED 2, ISCED 3C short), 3 - upper secondary (ISCED 3A-B, C long), 4 - post-secondary, non-tertiary (ISCED 4A-B-C), 5 - tertiary âĂŞ professional degree (ISCED 5B), 6, - tertiary âĂŞ bachelor degree (ISCED 5A), 7 - tertiary âĂŞ master/research degree (ISCED 5A/6), 8 - tertiary - bachelor/master/research degree (ISCED 5A/6), .N - not stated or inferred.

- **Non-STEM**: graduates enrolled in other educational programs such as: general programs, teacher training, humanities, language and arts, social sciences, business and law, agriculture and veterinary, health and welfare, and services.

Table A1 reports the number and percentage of people in the PIAAC survey after pooling all countries together. Total, Graduates, Non-Graduates, STEM and Non-STEM graduates refer to the categories described above. *All* refers to both genders (female and male). While the first row of this table reports information concerned to *All* people, disaggregated by educational group, the second and third row refer to the number and percentage of women and men in each group, respectively. The PIAAC sample is representative and balanced in terms of gender (around 45% female, and 55% male). As expected there are more non-graduates than graduates, and more adults with non-STEM professional degrees than with STEM degrees.

Table 2: Number and percentage of people in the PIAAC survey (pooling all countries together)

	Total		**Non-Graduates**		**Graduates**					
					All		**STEM**		**Non-STEM**	
All	85103	100%	49405	58.05%	35698	41.95%	10620	29.45%	24971	69.95%
Female	37993	44.64%	19824	40.13%	18169	50.90%	2627	24.74%	15493	85.27%
Male	47110	55.36%	29581	59.87%	17529	49.10%	7993	75.26%	9478	54.07%

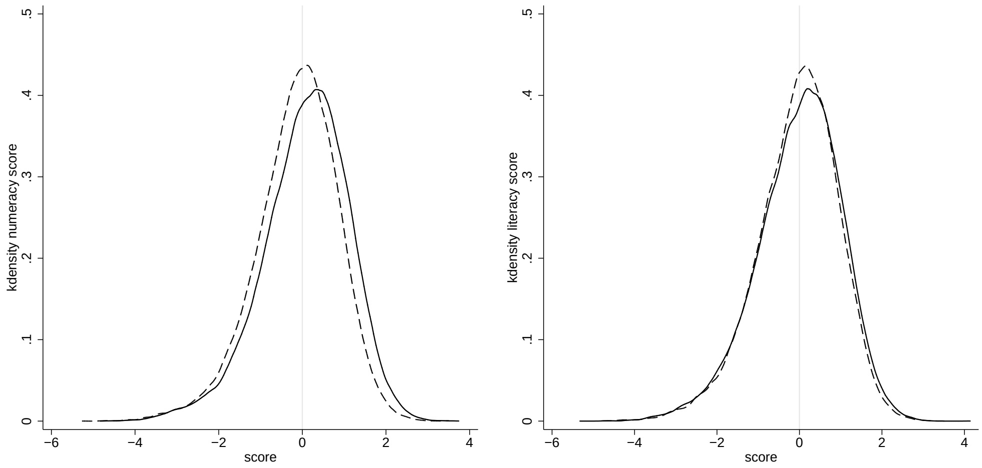
Source: PIAAC. Only full-time workers are considered. Percentages of STEM are computed as proportion of graduates. *All* people refers to both gender (female and male).

4.2 Skills

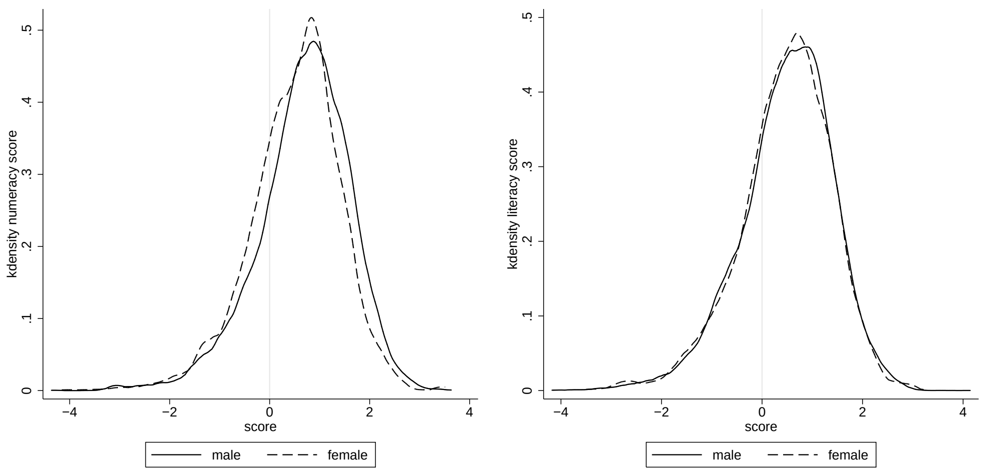
Most countries have an important proportion of adults who achieved low levels of proficiency in numeracy and literacy scores. Between 4.9% and 27.7% adults have the lowest literacy scores, and between 8.1% and 31.7% have the lowest numeracy scores (OECD 2013a).[15] Table A1 in the Appendix presents simple descriptive statistics of non-standardised measures of numeracy and literacy skills for each subgroup of the population. Standardised measures of skill scores are centered to mean zero and consider 1 standard deviation. They have been created to facilitate the interpretation of pooled coefficients across countries. Non-standardised measures of skill scores are used for single country analyses.

The distribution of numeracy skills varies between men and women. Similarly to Hanushek et al. (2015), baseline models are limited to full-time workers at the time of the survey in order to obtain a homogeneous sample of workers with strong labor-force commitment. Full-time employees are considered as those who work at least 30h per week. As one might expect, graduates have higher average scores of literacy and numeracy proficiencies than non-graduates. Figure 1(a) shows the distribution of numeracy and literacy scores for men and women for total full-time workers. In all groups of the analysis, men have a higher average of numeracy scores, but similar literacy scores with respect to women. For STEM graduates, there is no difference in numeracy scores (Figure 1(b)).

15. Many countries have larger proportions of population with low levels of proficiency on the problem solving in technology-rich environments (between 2.9% and 8.8%).



(a) Total



(b) STEM graduates

Figure 1: Distribution of numeracy and literacy skills
Notes: Source: PIAAC. Graphs use normalised measures of skill scores across all countries.

In order to understand better the relationship between numeracy and literacy skills, I analyse the correlation between these skills in the following section.

4.2.1 Correlations

There is a strong correlation between numeracy and literacy scores. For the total sample of full-time workers in PIAAC, this correlation is statistically significant and about 0.85. Non-graduates adults show higher correlation of numeracy and literacy scores than graduates. Although small, the difference between the correlation among graduates and non-graduates is significant (Table 3). Some personal characteristics of graduates in addition to the level of education may explain their lower correlation between literacy and numeracy skills compared to non-graduates. Those characteristics might include degree of specialization, age, experience, occupations, and industry at which they work that help them to develop and master numeracy and literacy skills.

Table 3: Correlation between numeracy and literacy skills $corr(n, l)$

	Total	**Non-Graduates**	**Graduates**			**Test**
		β_1	β_2	**STEM**	**Non-STEM**	$P(Ho: \beta_1 = \beta_2)$
All	0.8500^{***}	0.8372^{***}	0.7940^{***}	0.7997^{***}	0.7946^{***}	0.000
Female	0.8410^{***}	0.8301^{***}	0.7958^{***}	0.8011^{***}	0.7924^{***}	0.000
Male	0.8558^{***}	0.8459^{***}	0.8007^{***}	0.8031^{***}	0.8026^{***}	0.000

Source: PIAAC. Only full-time workers. *All* people refers to both gender (female and male).
Sample weights are considered. Column of the Test reports the probability to fail to reject the null hypothesis that the correlation between numeracy and literacy of graduates and non-graduates is the same.
$*p < 0.10, **p < 0.0, ***p < 0.01$

Given the close correlations between numeracy and literacy skills, one might wonder about the presence of multicollinearity, understood as the almost perfect linear combination of numeracy and literacy test scores in regression analysis. In presence of multicollinearity, regression model estimates become unstable and standard errors increased widely. For this reason, multicollinearity tests are carried out for the different model specifications used in this paper.[16] Results of the Variance Inflation Factor (VIF) show that numeracy and literacy test scores are not multi-collinear.[17] VIF coefficients are lower than 10. Table A2 in the Appendix reports the multicollinearity test for the basic model with different control variables.

4.3 Labour outcomes

Wages

The baseline measure of wages refers to gross hourly earnings of wage and salaried workers. Data has been obtained from the Public Use File for most of the countries. For Austria and Germany the Scientific Use Files have been requested from the PIAAC National centers. For other countries with missing information, I use the mean wage of each decile provided by Hanushek et al. (2015). Similarly to them, I assign the decile median to each survey participant belonging to the respective decile of the country-specific wage distribution.

16. Shomos and Forbes (2014) raised this concern when using Australian PIAAC data, but they did not test this hypothesis.
17. VIF is the commonly used multicollinearity test.

Wages are measured as individual hourly wages as described in the Appendix. Descriptive statistics of mean Purchasing Power Parity (PPP) wages across countries corrected by US dollars are presented in Table A1.

Since, the relationship between numeracy and literacy can vary across income groups, it is interesting to explore the correlation between these skills for different quantiles of the wage distribution. Also, as pointed out before, it is possible that higher actual wages lead to further skills' investments. Certainly, one would wonder if higher wages will lead to higher investments of a particular set of skills, or would actually lead to invest in both numeracy and literacy. In this article, I will not be able to disentangle the causal relationship between wages and skill acquisition. Instead, I will explore the relationship between these variables by studying how close they are correlated. Hence, Table 4 reports the correlation between wages and numeracy, wages and literacy, and the correlation between wages and both skills. Across the income distribution, correlation between numeracy and literacy skills is stable (0.82-0.86). Interestingly, wages and single skills (either numeracy or literacy) are positively and statistically significantly correlated for wages allocated between the 30% and 50% of the wage distribution. But the correlation between wages and the interaction between numeracy and literacy is positive and statistically significant only for these two top-income quantiles of the wage distribution.

Table 4: Correlation across wage quantiles

Wage quantile	$corr(num, lit)$	$corr(wage, num)$	$corr(wage, lit)$	$corr(wage, lit * num)$
$\tau_w = 10$	0.8303***	0.0516	0.0267	0.0091
$\tau_w = 30$	0.8413***	0.0421***	0.0312***	0.0007
$\tau_w = 50$	0.8359***	0.0463***	0.0536***	0.0160
$\tau_w = 70$	0.8213***	-0.0317	-0.0208	0.029***
$\tau_w = 90$	0.8662***	-0.1419	-0.1048	0.0549***

Source: PIAAC. Correlation considers all full-time workers.
Correlations consider individual weights. τ_w refers to a particular wage quantile.
$*p < 0.10, **p < 0.0, ***p < 0.01$.

5 Empirical Model

Cognitive skills were represented by a very general production function. Here I provide a more detailed definition of this production function allowing for the presence of an interactive term which measures joint skills, and then by using quadratic functions.

Cognitive skills are defined as a combination of numeracy and literacy skills. Intuitively, individuals with higher literacy and numeracy skills are more likely to be employed and they are also more likely to have higher wages than low skilled workers. It can also well be that higher numeracy scores are influenced by literacy levels, and vice versa. To capture these effects in this particular setting, the production of cognitive skills, $z_i = f(l_i, n_i)$, includes the joint effect of numeracy and literacy skills represented by the interaction term $l_i * n_i$:

$$z_i = \sigma_1 l_i + \sigma_2 n_i + \sigma_3 (l_i * n_i) \tag{8}$$

where l_i and n_i refer to the individual level of literacy and numeracy skills, respectively. As before, i refers to each individual. The partial effect of each skill (either numeracy or literacy) on labour outcomes can be determined by taking the first order partial derivative from equation 8. The partial contribution of literacy, for example, will depend on its independent contribution as well as the cross-effect of numeracy.[18] Equations 9 and 10 summarize these effects.

$$\frac{\partial z_i}{\partial l_i} = \sigma_1 + \sigma_3 n_i \tag{9}$$

$$\frac{\partial z_i}{\partial n_i} = \sigma_2 + \sigma_3 l_i \tag{10}$$

The complementarity or substitutability of numeracy and literacy clearly depends on the sign of the estimated coefficient of the interaction between those skills ($\hat{\sigma_3}$). If skills are complementary, the sign of $\hat{\sigma_3}$ is expected to be positive; if instead they are substitutes, the sign of $\hat{\sigma_3}$ will be negative. If numeracy and literacy are not related, the magnitude of $\hat{\sigma_3}$ will converge to zero.

Another feature to analyse is the concavity or convexity of marginal returns to skills.[19] Concave functions will be a sign of diminishing returns to skills. In other words, marginal improvements of skills will face a saturation point and will be highly beneficial for those with lower level of skills, but decreasingly profitable for those with higher levels of skills. Dougherty (2003) tested non-linearities of the impact of numeracy and literacy on wages and found convex functions for numeracy skills. He argued that marginal improvements in numerical skills benefit disproportionally those with highest ability. I test this hypothesis in the empirical section. Equation 11 captures the potential concavity or convexity of skills:

$$z_i = \beta_1 l_i + \beta_2 l_i^2 + \beta_3 n_i + \beta_4 n_i^2 \tag{11}$$

In this case, the marginal returns to numeracy and literacy will be determined as follows:

$$\frac{\partial z_i}{\partial l_i} = \beta_1 + 2\beta_2 l_i \tag{12}$$

$$\frac{\partial z_i}{\partial n_i} = \beta_3 + 2\beta_4 n_i \tag{13}$$

Empirically, marginal impacts to numeracy and literacy skills are estimated for men and women separately. Results are discussed in section 6.

This article concentrates on the analysis of wages as outcome variable. When relaxing the linearity assumption on the relationship between cognitive skills and wages but otherwise keeping the model exactly as it was presented in section 3, the empirical model of interest consists in a slightly modification of equation 6, which can be summarized in equation 14:

$$w_i = \alpha_0 + \phi_1 \; z_i + \phi_3 \; edu_i + \phi_4 \; (exp_i, exp_i^2) + \phi_5 \; \chi_i + \zeta_i \tag{14}$$

where, as before, w_i is the outcome variable (log wages) which varies across individuals i; edu_i, years of education, exp_i and exp_i^2 experience and experience squared, χ_i refers to background characteristics such as gender, civil status, having children, and parental background, z_i refers to the set of cognitive

18. This model differs from Shomos and Forbes (2014) by including numeracy and literacy as separately skills instead of using a compound measure.

19. Notice that word "returns" are used hereby to indicate the general impact of skills on wages, and not their causal effect. I acknowledge my PhD thesis committee for suggesting me to make explicit this remark.

skills (numeracy and literacy) and it is determined by equation 8 or equation 11, and ζ_i refers to the residual term.[20] The empirical specification also includes country, occupations (ISCO 2 codes), and industry (ISIC 1 codes) dummies. Similarly, as demonstrated in section 3, the estimated parameters ϕ_i measure the compound effect of unobserved skills and each individual variable (education, experience, and others) on wages.

To determine the average effects for all countries, regressions are estimated by pooling the data and performing the analysis on this sample. Country-specific estimates are obtained by computing similar regressions for each country separately. Analyses are performed separately for the groups defined in section 4.1.

Since estimated coefficients can vary in presence of other explanatory variables and when using diverse specifications, different wage models are employed to verify the results. First, the basic linear model that uses level of education and experience as main control variables (Tables 5, 10 and A12). In a second specification, I extend the basic model by including a set of control variables such as employment status of the partner, parental background, and having a small child (2 years old or younger) (Tables 8 and 9). Third, I look at the returns to skills across different standard cohorts (16-34, 35-54, and 55-65 years old). Table A3 reports estimates for adults in prime age. Fourth, I estimate the effect of skills for each income quantile (Table 7). They will estimate the conditional mean of numerical and literacy skills at each specific quantile of the wage distribution. Fifth, I run separate regressions for each country (Tables A6, A7, A8, A10, and A11). Sixth, I test the concavity or convexity of skill returns. Estimates of non-linear specifications are shown in Table 6.

6 Empirical results and Discussion

Table 5 reports a summary of the OLS estimation results of the main variables (numeracy, literacy) of the basic model, where the dependent variable refers to ln(wages), and the set of controls are experience, experience squared, and in case of columns 1 and 2, also education. Additional controls include country and occupational dummies. Estimates are computed separately for men and women. Odd columns show the results for men, while even columns show the results for women. Each pair of columns report the results for each population group: Total, Graduates, Non Graduates, STEM graduates, and Non-STEM graduates. Skill measures reported in these Tables are standardised scores with mean of zero and standard deviation of one across countries; therefore point estimates should be interpreted as the effect of a change in one standard deviation in skill scores on the average wage across countries.

As demonstrated in section 3, the estimated parameters presented here measure the compound effect of unobserved skills and each individual regressor. Across most specifications and different population groups, results from Table 5 show positive and statistically significant economic returns to numeracy and literacy skills. Moreover, estimates for the economic returns to numeracy skills are larger than those from literacy by factor of two or three. Across all population groups, the effect of numeracy on wages ranges from 5.4% to 6.8%, while the estimates of literacy fall between 1.4% to 4%. These

20. In the PIAAC survey civil status is captured by the dichotomous variable of living with the partner or spouse. For robustness, similar analysis has been carried out, including age and age squared as proxy of experiences, which confirmed these results.

results indicate that numeracy has a stronger role than literacy skills on wages. Additionally, this table shows that returns to numeracy skills are larger for graduates (6.8%) than for non-graduates (6% approx.). Also, for STEM graduates, numeracy seems to pay out less (5.7% approx.) than for Non-STEM graduates (6.8% approx.). This can be explained by reduced marginal returns to numeracy skills after having followed a STEM program. Contrarily, for Non-STEM graduates, their dexterity in numerical skills could explain the wage difference among graduates of similar fields. Magnitudes of estimates of numeracy and literacy skills are very similar between men and women within each population group.

These results contrast with the ones found previously in the literature (McIntosh and Vignoles 2001; Dougherty 2003) which suggested that an additional standard deviation in literacy skills was associated with larger earnings than in numeracy skills. These dissimilar results can be explained due to the time frame of the data used in those papers. McIntosh and Vignoles (2001) used data from the 1970 cohort interviewed in 2004, and the analysis of Dougherty (2003) used data of the NLSY respondents from 1988, 1992 and 1996 rounds. Finding larger returns to numeracy skills over literacy skills using PIAAC 2013 can reflect the strong impact of technology and computerization which change task requirements for jobs (Lindley 2012), rise demand for workers who perform abstract tasks and master numerical skills, and reward more their productivity. My results are in-line with Paglin and Rufolo (1990) and Murnane, Willett and Levy (1995) and other studies that use more recent data sets (Antoni and Heineck 2012; Hanushek et al. 2015).
As expected, returns to skills (numeracy and literacy) are larger for graduates than for non-graduates, since the former have larger levels of education and are likely to be employed in occupations that require larger numerical and literacy skills.

Although the impact of informational and technological skills (ICT) has become increasingly important with the technological change, in this article, I disregarded the analysis of ICT and focus only on the contribution of numeracy and literacy skills. The main reasons for excluding ICT skills from the analysis are the following: first, the traditional debate and the priority policies in terms of cognitive skills have been concentrated mainly on the contributions of numeracy and literacy. These are indeed competences needed for lifelong learnings. Second, the evidence on the role of numeracy and literacy skills is still far from conclusive. Finally, by excluding ICT measures, we are able to compare our estimates with single country studies which have focused only on numeracy and literacy skills.

Another important result from Table 5, also stable across different specifications, is the positive coefficient of the interaction between numeracy and literacy skills. However, when disaggregating in population subgroups, this estimate is only significant for female non-graduates (column 6). This result can be interpreted as the absence of a complementary effect of numeracy and literacy skills on wages, except for female non-graduates. The skill complementarity means that high proficiency levels of numeracy skills leads also to the achievement of higher levels of literacy skills and vice-verse.

This result can be explained with help of the theory of comparative advantage and specialization of labour skills. The international trade theory predicts that individuals (or countries) gain more when they specialize in producing goods at which they have comparative advantages. Similar reasoning applies here to understand the different effects for graduates and non-graduates. Graduates usually have higher levels of numeracy and literacy skills than non-graduates; then, results show that it is more profitable for graduates to specialize in the use of either numeracy or literacy than for non-graduates.

Gender differences in magnitude and statistical significance of *numeracyliteracy* among non-graduates can be interpreted in light of the literature that analyses the differences in the complementarity of tasks and technical change across gender. For instance, Lindley (2012) shows that a large range of tasks complementary to technical change are undertaken by men but not by women. She also found a large male bias in numeracy test scores independent of the level of education. This suggests that specialization can be more fruitful in terms of wages for men than for women.

The learning process and skill accumulation vary with age. On average, young children learn easily and older persons learn less fast but achieve high levels of skills. In the labour market, experience and tenure will also affect skill scores. For these reasons, one can expect that economic returns to skills vary by age (Cunha, Heckman and Lochner 2006). When further splitting the sample by age cohorts, similar results to the ones obtained before are found for prime age workers (35-54 years). See table A3 for details. However, similar evidence for other age cohorts was not statistically significant: entry-age (25-34 years) and exit-age (55-65 years). As pointed out by Hanushek et al. (2015), this might be because returns to skills increase steadily with age until age 35 and they get only slightly smaller beyond 55 years.

Different approaches that include instrumental variables and differences-in-differences (Diff-in-Diff) are now commonly used to identify the causal relationship of skills on wages. Hanushek and Woessman (2012b), for example, carried out three different ways to interpret the strong relationship between cognitive skills and growth.[21] First, they use institutional school policies (such as the impact of varying Catholic church history) as instrument for identifying skill variation (see also Hanushek and Woessman (2012a)). Second, following Hanushek and kimko (2000), Hanushek and Woessman (2012b) implement a Diff-in-Diff approach to identify the reverse causality as well as the potential relationship between cultural differences or economic institutions of national economies that could be correlated with favourable educational outcomes (Hanushek and Woessman 2012b, p. 6). Specifically, this approach compares the returns to skills of immigrants schooled in their country of origin to those of immigrants from the same country schooled within the United States. And finally, they exploit a longitudinal data of test scores to analyse changes in growth rates by eliminating stable country-specific factors.

Given the cross-sectional dimension of the PIAAC data, and that this study does not use any additional dataset, it has not been possible to asses causality in this framework.

6.1 Non-linear returns to skills

From the previous section we have learnt that numeracy and literacy skills matter for wages. For this reason, an interesting feature to investigate is the concavity or convexity of returns to skills. The argument to test the non-linear impact of numeracy and literacy skills relies on the idea that skill increment can benefit people differently across the skill distribution.

Table 6 shows the results from equation 11, which adds a quadratic term of each skill in the specification of the skill production function. Regressions include control variables used in the basic model. Coefficients of linear terms of skills are positive and statistically significant for men and women in

21. Although variables such as growth and wages are different, they share similarly a positive relationship with skills and they generate similar skepticism about the identification of their causal effects.

Table 5: Basic Regressions

	Total		Graduates		Non Graduates		STEM Graduates		Non-STEM Graduates	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women	(7) Men	(8) Women	(9) Men	(10) Women
Numeracy	0.057***	0.057***	0.068***	0.068***	0.060***	0.062***	0.059***	0.054**	0.068***	0.069***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.007)	(0.009)	(0.013)	(0.022)	(0.013)	(0.009)
Literacy	0.020***	0.021***	0.033***	0.036***	0.014*	0.014*	0.035**	0.028	0.040***	0.036***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.007)	(0.008)	(0.013)	(0.022)	(0.013)	(0.009)
Numeracy*Literacy	0.003	0.006*	0.000	0.002	0.002	0.009**	0.002	-0.010	-0.004	0.004
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.006)	(0.010)	(0.006)	(0.006)
Country, Occupation FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	32655	29677	14541	16103	18114	13574	6793	2349	7748	13754

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sample weights. Dependent variable: log gross hourly wage. Sample: full-time workers graduates (Canada includes part-time workers). Experience and experience squared, and education in models (1) and (2) are included as control variables.

all population groups (total, graduates and non-graduates). Also, positive squared coefficients of numeracy skills for females in all groups are found, but those are only statistically significant among all women in the total population (column 3) and non-graduates (column 9). Squared estimates of literacy skills are positive and statistically significant for men who did not graduate. The quadratic terms are only statistically significant among non-graduates, and very different for men and women. While the quadratic term of numeracy skills is only statistically significant for women, the quadratic term of literacy skills is only statistically significant for men. In both cases the sign of these quadratic estimates is positive. Table A4 confirms the stability of the results by including additional control variables. These results are interesting because now one can infer that incremental skills worth to men and women particularly non-graduates. Among this group, incremental returns to literacy skills are worthier for men, while incremental returns to numeracy are worthier for women. Thus, these results are in line with figure 2, which shows additionally a strong difference in the skill-return function between graduates and non-graduates.[22]

6.2 Heterogeneous returns to skills

Returns to numeracy and literacy skills are heterogeneous: they vary across the income distribution and across countries. In this section, I analyse the returns to skills across these two different dimensions.

First, Table 7 reports the different returns to skills across the within country wage distribution for all population groups analysed in the study. Column (1) shows mean estimates for each population group (across countries), and columns (2-6) show the estimates conditional to a particular wage quantile indicated by each τ_u, respectively. Quantiles of these latter columns refer to the within-country distribution of wages rather than the overall (pooled) distribution. Results show positive and statistically significant estimates for coefficients of numeracy skills across all wage quantiles. Literacy estimates are also positive in all quantiles but only significant among graduates. Mean literacy estimates are significant across all population groups. Furthermore, estimates of numeracy are larger than those from literacy skills for all mean estimates and for most quantiles of the wage distribution. These results confirm previous findings that suggested that numeracy has larger returns than literacy skills.

An interesting result obtained from this analysis is that, estimates to *numeracy*literacy* are not statistically different than zero for all population groups, which confirm the hypothesis that the combination of those skills do not impact on wages. A striking exception is the case of top income graduates for whom the interaction of numeracy and literacy skills results to be negative and statistically significant. This result can be interpreted as for top income graduates it pays off more to specialize.[23]

Similarly, Table A5 shows the different returns to the interaction between numeracy and literacy skills separately for men an women. Figure A3 shows graphically those returns.

Second, I am interested in investigating the heterogeneity of returns to skills across countries. Hanushek et al. (2015) found heterogeneous returns to skills for different countries, but they only used one meas-

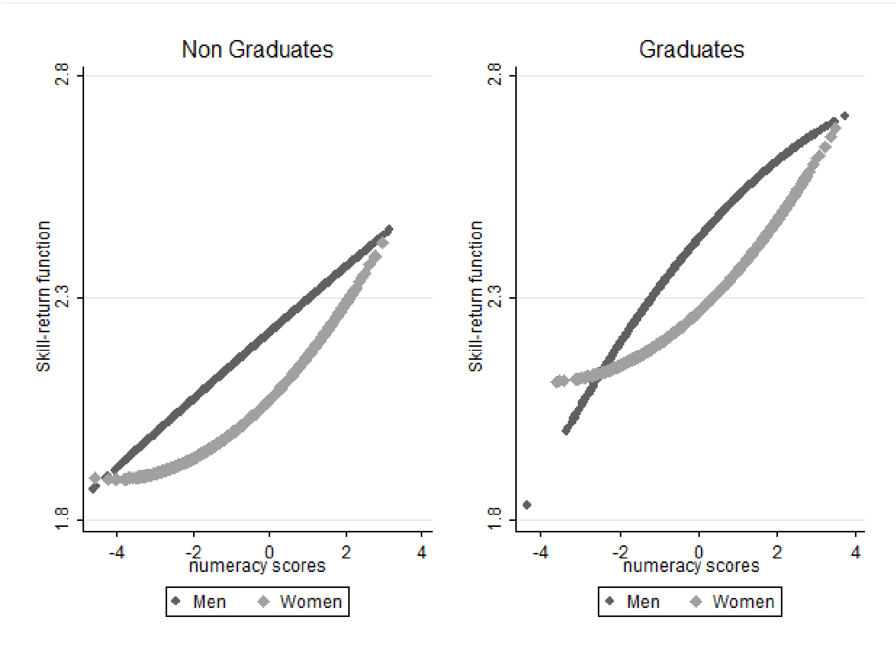
22. Figure A1 shows the concavity or convexity of numeracy and literacy skills for STEM and Non-STEM graduates.

23. One could explore further the relationship between wage inequality and skills. For instance, Paccagnella (2015) showed a negative correlation between measures of skills and wage inequality using the PIAAC data.

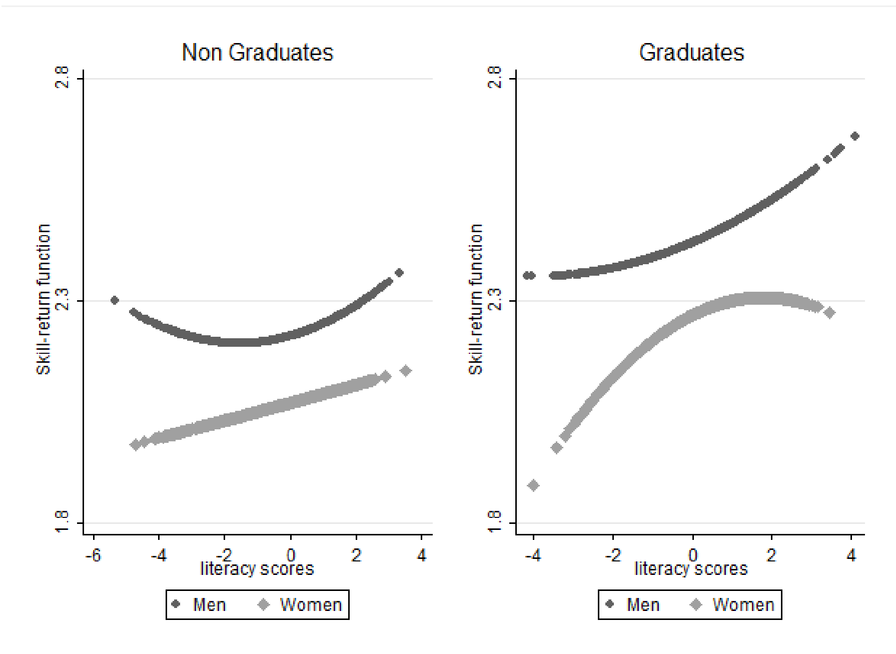
Table 6: Non linearities in numeracy and literacy skills

	Total			Graduates			Non-Graduates		
	All	Men	Women	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numeracy	0.101***	0.072***	0.072***	0.128***	0.107***	0.089***	0.110***	0.080***	0.094***
	(0.004)	(0.006)	(0.006)	(0.008)	(0.012)	(0.010)	(0.006)	(0.007)	(0.009)
Literacy	0.004	0.024***	0.022***	0.023***	0.039***	0.048***	0.006	0.023***	0.022***
	(0.004)	(0.006)	(0.006)	(0.008)	(0.012)	(0.010)	(0.006)	(0.007)	(0.008)
Numeracy^2	0.010***	0.004	0.013***	0.003	-0.007	0.008	0.004	-0.002	0.010**
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)
Literacy^2	0.007***	0.009***	0.002	-0.001	0.005	-0.011*	0.008***	0.008**	0.002
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.003)	(0.004)	(0.005)
Observations	70968	38035	32933	30699	14571	16128	40748	23754	16994
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Dependent variable: log gross hourly wage. Additionally, education is included in models (1), (2), and (3). Similar results are obtained when including partner status and parental background as additional control variables in all specifications.



(a) Returns to Numeracy skills



(b) Returns to Literacy skills

Figure 2: Concavity or convexity of numeracy and literacy skills
Notes: Source: PIAAC. Graphs are based on non-linear estimations described in section 6.1

Table 7: Quantile effects, treating education and skills as exogenous

	Total					
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	τ_u=0.10	τ_u=0.30	τ_u=0.50	τ_u=0.70	τ_u=0.90
Female	-0.160***	-0.032	-0.056***	-0.065***	-0.079***	-0.084***
	(0.005)	(0.018)	(0.011)	(0.010)	(0.008)	(0.007)
Numeracy	0.057***	0.030	0.062***	0.061***	0.066***	0.063***
	(0.006)	(0.019)	(0.012)	(0.010)	(0.008)	(0.008)
Literacy	0.015**	0.025	0.003	0.007	0.009	0.012
	(0.006)	(0.019)	(0.012)	(0.010)	(0.008)	(0.008)
Num*Lit	0.001	-0.000	0.003	0.000	-0.002	-0.001
	(0.002)	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)
Education	0.049***	0.015***	0.032***	0.037***	0.039***	0.042***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
	Graduates					
	Mean	τ_u=0.10	τ_u=0.30	τ_u=0.50	τ_u=0.70	τ_u=0.90
Female	-0.138***	-0.055	-0.046**	-0.052***	-0.062***	-0.069***
	(0.006)	(0.029)	(0.015)	(0.013)	(0.010)	(0.010)
Numeracy	0.070***	0.047	0.062***	0.065***	0.074***	0.070***
	(0.006)	(0.028)	(0.015)	(0.013)	(0.010)	(0.010)
Literacy	0.034***	0.026	0.026	0.034**	0.037***	0.042***
	(0.006)	(0.028)	(0.014)	(0.013)	(0.010)	(0.010)
Num*Lit	-0.001	-0.018	-0.006	-0.008	-0.013**	-0.013**
	(0.003)	(0.013)	(0.007)	(0.006)	(0.005)	(0.005)
	Non Graduates					
	Mean	τ_u=0.10	τ_u=0.30	τ_u=0.50	τ_u=0.70	τ_u=0.90
Female	-0.171***	-0.023	-0.066***	-0.074***	-0.082***	-0.087***
	(0.006)	(0.016)	(0.012)	(0.009)	(0.009)	(0.008)
Numeracy	0.059***	0.021	0.050***	0.054***	0.053***	0.051***
	(0.006)	(0.015)	(0.011)	(0.008)	(0.008)	(0.007)
Literacy	0.016**	0.013	0.004	0.001	0.003	0.004
	(0.005)	(0.015)	(0.011)	(0.008)	(0.008)	(0.007)
Num*Lit	0.004	0.005	0.002	-0.003	0.000	-0.001
	(0.002)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)
	STEM					
	Mean	τ_u=0.10	τ_u=0.30	τ_u=0.50	τ_u=0.70	τ_u=0.90
Female	-0.161***	-0.005	-0.055	-0.083*	-0.111***	-0.102***
	(0.017)	(0.089)	(0.045)	(0.040)	(0.032)	(0.028)
Numeracy	0.061***	0.126	0.051	0.052	0.054*	0.071***
	(0.013)	(0.064)	(0.033)	(0.029)	(0.023)	(0.020)
Literacy	0.028*	-0.059	0.007	0.025	0.030	0.026
	(0.013)	(0.065)	(0.033)	(0.030)	(0.023)	(0.021)
Num*Lit	0.001	0.021	0.025	0.011	0.000	0.001
	(0.006)	(0.027)	(0.014)	(0.012)	(0.010)	(0.009)
	Non-STEM					
	Mean	τ_u=0.10	τ_u=0.30	τ_u=0.50	τ_u=0.70	τ_u=0.90
Female	-0.133***	-0.046	-0.036	-0.021	-0.023	-0.029
	(0.010)	(0.042)	(0.024)	(0.018)	(0.015)	(0.015)
Numeracy	0.072***	0.021	0.070*	0.075***	0.100***	0.094***
	(0.013)	(0.052)	(0.030)	(0.022)	(0.019)	(0.018)
Literacy	0.029*	0.050	0.018	0.025	0.018	0.018
	(0.013)	(0.051)	(0.030)	(0.022)	(0.019)	(0.018)
Num*Lit	-0.004	-0.011	-0.007	-0.003	-0.012	-0.009
	(0.006)	(0.024)	(0.014)	(0.010)	(0.009)	(0.008)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: log gross hourly wage. τ refers to a particular quantile of the wage distribution.
Column (1) shows estimates across wages, while columns (2)-(6) show quantile estimates within-country wage distribution. Regressions control for education experience, experience squared. Models for total people control additionally for years of education. Wage quantiles refer to the within-country distribution of wages. All models consider 50 weighted least-squares iterations before doing the linear programming iterations (wls=50).

ure of skills in their evaluations.[24] After replicating the basic model reported in Table 5, I run similar regressions for each country similarly to Hanushek et al. (2015). In line with this study, my results confirm that returns to numeracy are heterogeneous between countries, as well as returns to literacy skills. Also, when looking at the potential complementarity between numeracy and literacy skills, results vary across countries. Only Austria, Czech Republic, France and UK have positive interaction coefficients of literacy and numeracy. Analyses for individual countries do not show conclusive evidence for skill complementarity among female non-graduates (see Table A9). The differences between countries might be due to different institutional settings (Hanushek et al. 2015). Future research will try to understand the drivers of these differences. Returns to numeracy are larger than returns to literacy in many countries as it was found for the average effects. Estimated numeracy coefficients are larger than literacy coefficients across all population groups. Country specific results are reported in the Appendix as follows: when consider the total sample (Table A6), only graduates (Table A7) and only non-graduates (Table A8).

6.3 Female wage penalty

A well established literature states that men and women do not differ substantially in their verbal and numerical abilities (Lindberg et al. 2010; Niederle and Vesterlund 2010). Our previous results confirm that skills differences do not explain the gender wage gap.

Gender discrimination has not been modeled in this article; however, the gender differences in wages that remain unexplained could be attributed to the female dummy included in the empirical set-up. To study how the economic returns differ across gender, this section investigates particularly this female estimate. Results of the basic model are presented in Table 8. Also, since other variables, such as employment status of the partner, parental background, having a small child (2 years old or younger) and industry dummies are particularly important for estimating gender wage differences, they are included as additional control variable.

The last row of Table 8 reports negative and statistically significant estimates of *Female*, a dummy variable that takes the value of 1 in case a person is woman or 0 in case of man. Thus, they indicate a persistent female wage penalty across all population groups (total, graduates, STEM, and non-STEM graduates). Columns 11 and 12 of Table 8 show negative and statistically significant estimates for the interaction variable of *Female*STEM*, which confirm the wage cost of women even among STEM graduates, despite the similar numerical and verbal skill distribution between gender (Figure 1). Table A12 shows sign and magnitudes of interacted coefficients of *Female* and *STEM* dummy variables, as well as other variables included in the basic model for graduates. A similar female wage penalty is found across specifications for single country analysis. Female penalty exists in most countries, even among STEM graduates (Table A10, A11).

Finding similar skill distributions (and potentially similar combination of skills) between men and women but stable female wage penalties is a worrying paradox. Adding different control variables to the basic model helps to rule out those factors as potential drivers of gender discrimination; however, they do not explain the sources of the gender wage differences. For Gneezy, Niederle and Rustichini

24. In most of their specifications, they report returns to numeracy, but they reported having found similar heterogeneous results when using literacy instead. Nevertheless, they did not report the use of both skills measures nor compare the magnitude of returns in their country-specific regressions.

(2003), gender wage gap is explained by individual's performance in competitive environments, and not by levels of skills themselves. Further analysis must try to understand the sources of this unexplained female wage gap. For instance, one possible explanation can be the composition of labour in particular occupations, and the intensity of using abstract, routine and manual tasks. This hypothesis could be explored by using a model that interacts wages gap with the dominant task components (routine, abstract, manual) of different occupations.

In Table 9, I replicate the estimates of Table 5 including more control variables and industry fixed effects. Additionally to education, models from Table 9 include experience and experience squared, variables such as employment status of the partner, parental background, and having an small child (2 years old or younger) and analytic weights. Magnitude of estimated coefficients of skills differ slightly from the basic model, but the sign, statistical significance and the magnitude of point estimates with respect to each other remain. Results from Table 9 confirm the larger economic returns to numeracy compared to literacy, and the complementarity of numeracy and literacy skills for female non-graduates.[25]

6.4 Returns to skills vs. returns to schooling

In this section, I compare the returns to cognitive skills with returns to education.

The literature establishes that the effect of education on earnings is positive and of relatively larger magnitude than returns to other investments (Harmon, Oosterbeek and Walker 2003). Using the International Social Survey Programme (ISSP) data of 1995 which combines different national surveys, these authors found that returns to schooling in Europe are about 6% approximately.[26] Country-specific estimates range between 3.9% to 14% for women, and between 4% to 8% for men.

A typical wage regression based on PIAAC data that includes numeracy yields returns to schooling of similar magnitude (5.9% approx.) (Hanushek et al. 2015).[27] Estimates from my model, which includes numeracy, literacy, and the interaction of both, go along with these findings. Columns (1) and (2) from Table 10 show that estimates, proxies for returns to education, are about 6.3% for men and 7% for women, which can be an indication of no serious bias in my specifications.

Mean estimates to returns to numeracy skills are higher than returns to education and account for about 7% of the wage variation. After controlling for occupation, numeracy estimates reduce in approximately 1.7%. Returns to literacy are smaller and about 2%. Interestingly, when controlling for occupations, both returns to numeracy and literacy are identical for men and women (Columns (3) and (4), Table 10).

It is also well documented that returns to education are not the same for everybody. Webber (2014) stresses that returns to education differ substantially across different fields of study, and there is

25. External validity of the results here should be treated with some precaution because the analysis only considers full-time workers. Mulligan and Rubinstein (2008) argue that increments in returns to skills from 70's to 90's change the labour force participation patterns of women and consequently the observed gender wage gap. Intrinsic characteristics of people who select themselves to work full-time might be related to their skill composition but are not accounted for in this study.

26. These authors include age, plant size and union, children and marriage, part-time work, year, region and industry dummies as control variables.

27. In this case, wage regressions include additionally experience, experience squared, and country fixed effects as control variables.

Table 8: Robust checks: Regressions with more control variables

	All people		Graduates		Non Graduates		STEM Graduates		Non-STEM Graduates		Graduates with STEM dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Numeracy	0.047***	0.047***	0.052***	0.052***	0.057***	0.056***	0.048***	0.047***	0.046***	0.047***	0.049***	0.049***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(0.007)	(0.012)	(0.012)	(0.010)	(0.010)	(0.008)	(0.008)
Literacy	0.023***	0.023***	0.041***	0.041***	0.014**	0.014**	0.045***	0.044***	0.043***	0.044***	0.043***	0.043***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(0.007)	(0.012)	(0.012)	(0.010)	(0.010)	(0.008)	(0.008)
Literacy*Numeracy	0.004***	0.003*	0.001	0.002	0.005**	0.004	0.004	0.007	0.001	-0.002	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)
Fem*Num	-0.002	-0.002	0.010	0.010	-0.015	-0.014	0.007	0.013	0.021	0.020	0.014	0.015
	(0.007)	(0.007)	(0.011)	(0.011)	(0.010)	(0.010)	(0.025)	(0.026)	(0.013)	(0.013)	(0.011)	(0.011)
Fem*Lit	0.009	0.009	0.005	0.006	0.007	0.008	0.016	0.023	-0.002	-0.004	0.002	0.003
	(0.007)	(0.007)	(0.011)	(0.011)	(0.010)	(0.010)	(0.024)	(0.025)	(0.013)	(0.013)	(0.011)	(0.011)
Fem*Num*Lit		0.003		-0.001		0.003		-0.015		0.005		-0.001
		(0.003)		(0.005)		(0.005)		(0.013)		(0.006)		(0.005)
STEM											0.018**	0.018**
											(0.008)	(0.008)
Female*STEM											-0.040***	-0.040***
											(0.013)	(0.013)
Female	-0.166***	-0.169***	-0.156***	-0.155***	-0.190***	-0.191***	-0.189***	-0.183***	-0.147***	-0.149***	-0.146***	-0.145***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.006)	(0.007)	(0.017)	(0.018)	(0.008)	(0.009)	(0.008)	(0.008)
P(Lit*Num + Fem*Num*Lit)=0		0.015***		0.870		0.091*		0.479		0.549		0.776
Country, Occ. and Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	37857	37857	18895	18895	18962	18962	5697	5697	13198	13198	18895	18895

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models include only full-time workers.
All models control additionally for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), and a constant.
Models (1) and (2) controls additionally for years of education.
Models (11) and (12) only include graduates.

Table 9: Regressions by gender (with more control variables)

	All people		Graduates		Non Graduates		STEM Graduates		Non-STEM Graduates	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)	Men (9)	Women (10)
Numeracy	0.067***	0.063***	0.049***	0.063***	0.058***	0.046***	0.048***	0.047**	0.042***	0.066***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)	(0.012)	(0.022)	(0.012)	(0.008)
Literacy	0.032***	0.033***	0.050***	0.036***	0.015**	0.013*	0.051***	0.039*	0.055***	0.034***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)	(0.012)	(0.021)	(0.011)	(0.008)
Literacy*Numeracy	0.010***	0.015***	0.002	0.002	0.003	0.007*	0.007	-0.010	-0.005	0.004
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.011)	(0.005)	(0.004)
Observations	19591	18266	9134	9761	10457	8505	4314	1383	4820	8378
Country, Occupation and Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models include a constant, and control for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger).
Models (1) and (2) controls additionally for years of education.

mixed evidence on the differences of schooling returns across types of institution. Since the choice of schooling investments (i.e. decision to attend college and to pursue a particular academic degree) is not random, our empirical models estimate the effect of skills conditional on a particular level of education (graduates, non-graduates, STEM and Non-STEM graduates). Results show that returns to skills vary slightly among different educational groups.

7 Conclusions

This paper quantifies the contributions of numeracy and literacy skills and their joint effects on earnings. It determines the impact of skills on wages across different population groups (all people, graduates, non-graduates, and STEM and non-STEM graduates). It shows that both numeracy and literacy skills matter significantly for men and women. It also pins down if women are penalized in the labour market by examining groups with homogeneous skill distributions such as those graduated from STEM programs.

A simple theoretical framework intends to shed light on the interpretation of the estimated coefficients. Results show higher returns for numeracy than for literacy skills across all populations groups. Technological change and computerization have risen the demand for numerical skills, which appears to explain this result. There is little complementarity among numeracy and literacy skills. The interaction of numeracy and literacy is positive and statistically significant only among female non-graduates. The study found graduates to have higher levels of numeracy and literacy skills than non-graduates. This result is explained because it seems more profitable for the former to specialize in the use of either numeracy or literacy than for latter ones.

An interesting but worrying result across all specifications (including pooled, quantile, and country-specific regressions) shows that skill differences do not explain wage gap. Women receive a wage penalty even among STEM graduates, a group in which men and women have similar skill distributions. Differences in non-linear skill-return functions between men and women bring new insights for understanding these differences in returns to cognitive skills. Quantile estimations confirmed these findings.

To complement this analysis, future avenues of research can explore differences in returns to skills across occupations. Also, it will be worth to study the links between the convexity or concavity of the skill-return functions and their complementarity. Furthermore, one can examine how migration can change country-specific returns to skills in the country of origin and the receiving country. With the availability of new longitudinal data and other sources, one will able to tackle the potential endogeneity of education and skill measures. Finally, it will be crucial to investigate the role of numeracy and literacy for educational achievements and their returns on labour outcomes, such as employment.

Table 10: Basic regressions by gender (detailed all controls)

	Total				Graduates				Non Graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exp	0.019***	0.017***	0.017***	0.015***	0.022***	0.017***	0.019***	0.016***	0.017***	0.014***	0.016***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp^2	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Numeracy	0.074***	0.077***	0.057***	0.057***	0.098***	0.096***	0.068***	0.068***	0.074***	0.087***	0.060***	0.062***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.007)	(0.009)
Literacy	0.027***	0.023***	0.020***	0.021***	0.045***	0.037***	0.033***	0.036***	0.024***	0.023***	0.014*	0.014*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
Num*Lit	0.003	0.004	0.003	0.006*	0.000	-0.001	0.000	0.002	0.004	0.011***	0.002	0.009**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
Education	0.063***	0.070***	0.046***	0.054***								
	(0.002)	(0.002)	(0.002)	(0.002)								
Constant	1.520***	1.335***	1.899***	1.505***	2.461***	2.430***	2.525***	2.563***	2.305***	2.216***	2.518***	2.202***
	(0.022)	(0.023)	(0.073)	(0.049)	(0.018)	(0.019)	(0.110)	(0.053)	(0.012)	(0.014)	(0.082)	(0.068)
Observations	32,655	29,677	32,655	29,677	14,541	16,103	14,541	16,103	18,114	13,574	18,114	13,574
R-squared	0.967	0.964	0.970	0.967	0.964	0.954	0.968	0.958	0.969	0.972	0.971	0.975
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Occupation FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time workers (Canada includes part-time workers).

Table 10 (continuation): Basic regressions by gender (detailed all controls)

	Graduates							
	STEM				Non STEM			
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	Men	Women	Men	Women	Men	Women	Men	Women
Exp	0.021***	0.019***	0.020***	0.017***	0.022***	0.017***	0.019***	0.016***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Exp^2	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Numeracy	0.075***	0.085***	0.059***	0.054**	0.108***	0.096***	0.068***	0.069***
	(0.014)	(0.024)	(0.013)	(0.022)	(0.014)	(0.010)	(0.013)	(0.009)
Literacy	0.055***	0.039	0.035**	0.028	0.045***	0.036***	0.040***	0.036***
	(0.014)	(0.024)	(0.013)	(0.022)	(0.014)	(0.010)	(0.013)	(0.009)
Num*Lit	0.003	-0.012	0.002	-0.010	-0.006	0.002	-0.004	0.004
	(0.007)	(0.011)	(0.006)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	2.454***	2.170***	2.528***	2.085***	2.476***	2.459***	2.522***	2.647***
	(0.027)	(0.055)	(0.231)	(0.095)	(0.025)	(0.020)	(0.102)	(0.068)
Observations	6,793	2,349	6,793	2,349	7,748	13,754	7,748	13,754
R-squared	0.968	0.959	0.972	0.964	0.960	0.954	0.964	0.957
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Occupation FE	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions use sampling weights. Dependent variable: log gross hourly wage. Sample: full-time workers (Canada includes part-time workers).

8 Appendix

Variables description

- **Wages**: refers to the gross hourly earnings of wage and salaried workers. They excluded bonuses and are PPP corrected by US dollars. In computations, following Hanushek et al. (2015), measures of wages refer to trimmed hourly wages (continuous if possible, otherwise deciles).
- **Education:** highest level of education obtained imputed into years of education. Derived variable in PIAAC.
- **Literacy:** Plausible literacy score 1 in PIAAC. It takes values from 0 to 500.
- **Numeracy:** Plausible numeracy score 1 in PIAAC. It takes values from 0 to 500.
- **Experience:** years of paid work during lifetime.
- **Age child:** age of the youngest child: (1) aged 2 or younger, (2) aged 3-5, (3) aged 6-12, (4) aged 13 or older.
- **Partner:** dummy variable referring to the condition of living with spouse or couple. It takes the value: 1 (yes), 0 (no).
- **Partner status:** categorical variable that refers to the work situation of spouse or partner. It could be unemployed (0), full-time (1), part-time (2), or other (3).
- **Parental background:** categorical variable referring to the highest level of education of the parents: neither parent has attained upper secondary (0), at least one parent has attained secondary school (1), at least one parent has attained tertiary education (3).
- **Number of books at home:** Having books at home: (1) 10 books or less, (2) 11 to 25 books, (3) 26 to 100 books, (4) 101 to 200 books, (5) 201 to 500 books, (6) more than 500 books.
- **Occupational dummies:** occupational classification of respondent's current job at 2-digit level (ISCO 2008).
- **Industry dummies:** Industry classification of respondent's job at 2-digit level (ISIC rev 4).

Table A1: Descriptive Statistics

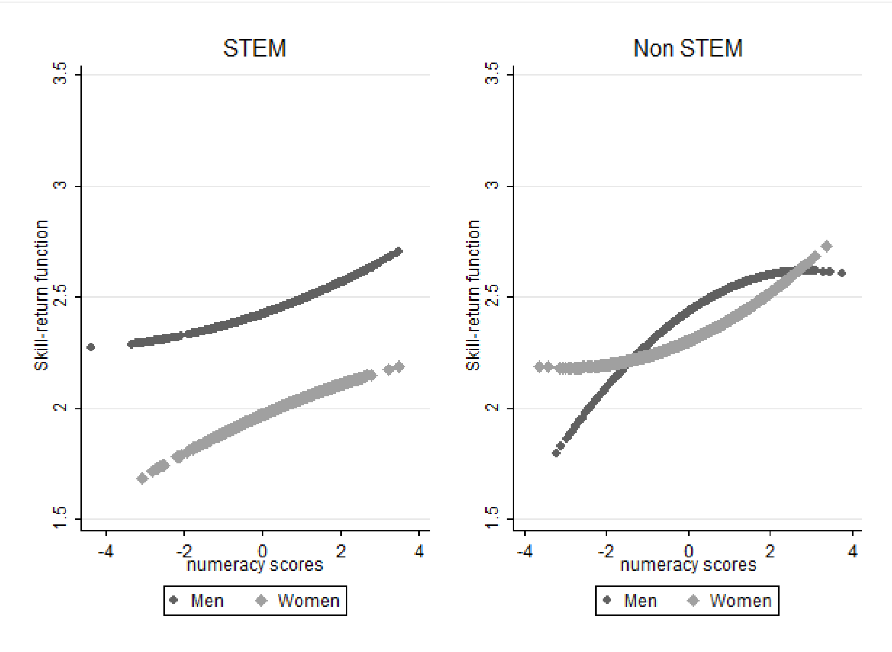
	Numeracy scores					Literacy scores				Wages		
	N	**Mean**	**sd**	**min**	**max**	**Mean**	**sd**	**min**	**max**	**N**	**Mean**	**sd**
Total	85096	276.71	49.69	44.29	462.95	278.74	45.34	30.06	446.45	88947	16.95	18.45
Men	47106	280.70	51.17	44.29	450.09	278.24	46.51	30.06	446.45	43325	18.28	18.89
Women	37990	271.77	47.32	45.26	462.95	279.36	43.83	58.20	432.59	45620	15.69	17.93
Graduates	35697	297.11	44.12	55.41	462.95	298.09	39.93	65.34	446.45	36858	20.65	17.32
Men	17528	305.42	44.38	65.92	450.09	300.49	40.61	65.34	446.45	16109	22.88	17.85
Women	18169	289.11	42.35	55.41	462.95	295.77	39.12	102.90	432.59	20747	18.91	16.69
Non Graduates	49399	261.97	48.25	44.29	428.55	264.76	43.85	30.06	440.20	52089	14.40	18.77
Men	29578	266.05	49.26	44.29	428.55	265.06	44.73	30.06	440.20	27216	15.55	18.95
Women	19821	255.88	46.04	45.26	418.27	264.31	42.50	58.20	410.92	24873	13.00	18.47
STEM	10620	308.07	44.74	65.92	462.95	301.37	40.96	65.34	438.64	10471	21.55	16.71
Men	7993	310.38	44.76	65.92	450.09	301.55	41.14	65.34	438.64	7446	22.90	16.70
Women	2627	301.05	43.93	88.24	462.95	300.81	40.42	125.46	421.17	3025	18.22	16.25
NON-STEM	24970	292.57	42.92	55.41	448.53	296.80	39.30	86.32	446.45	26263	20.32	17.57
Men	9477	301.42	43.50	88.57	448.53	301.42	43.50	88.57	448.53	8611	22.30	18.82
Women	15493	287.15	41.65	55.41	439.00	287.15	41.65	55.41	439.00	17651	19.06	16.78

Source: PIAAC. Only full-time workers. All countries excluding Russia.
Non standardised measures of numeracy and literacy scores.
Wages hourly earnings excluding bonuses for wage and salary earners, PPP corrected by US dollars (derived). See details in Variables description.

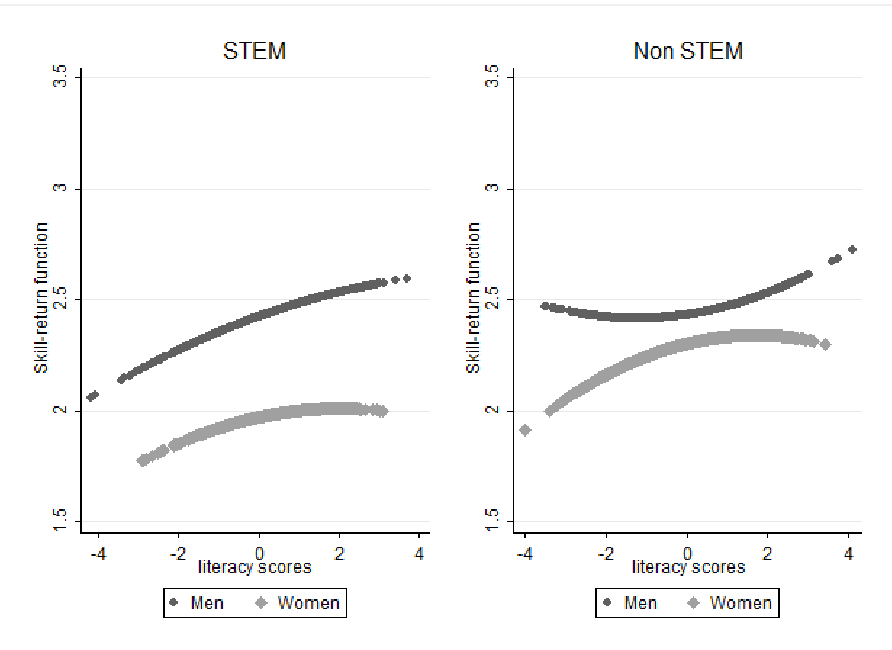
Table A2: Multicollinearity Test

	All people		Graduates		Non graduates		Graduates STEM		Graduates Non STEM	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Numeracy	6.05	0.1653	5.82	0.1717	5.35	0.1868	4.07	0.2458	7.48	0.1337
Literacy	6.01	0.1663	5.80	0.1725	5.29	0.1889	3.82	0.2620	7.45	0.1341

All models consider only full-time workers and basic specifications. Control variables include education, experience, experience squared, occupational country dummies, and a constant. Similar results are obtained from other test specifications.



(a) Returns to Numeracy skills



(b) Returns to Literacy skills

Figure A1: Concavity or convexity of numeracy and literacy skills
Notes: Source: PIAAC. Graphs are based on non-linear estimations described in section 6.1.

Table A3: Regressions by age: adults with age 35-54 years

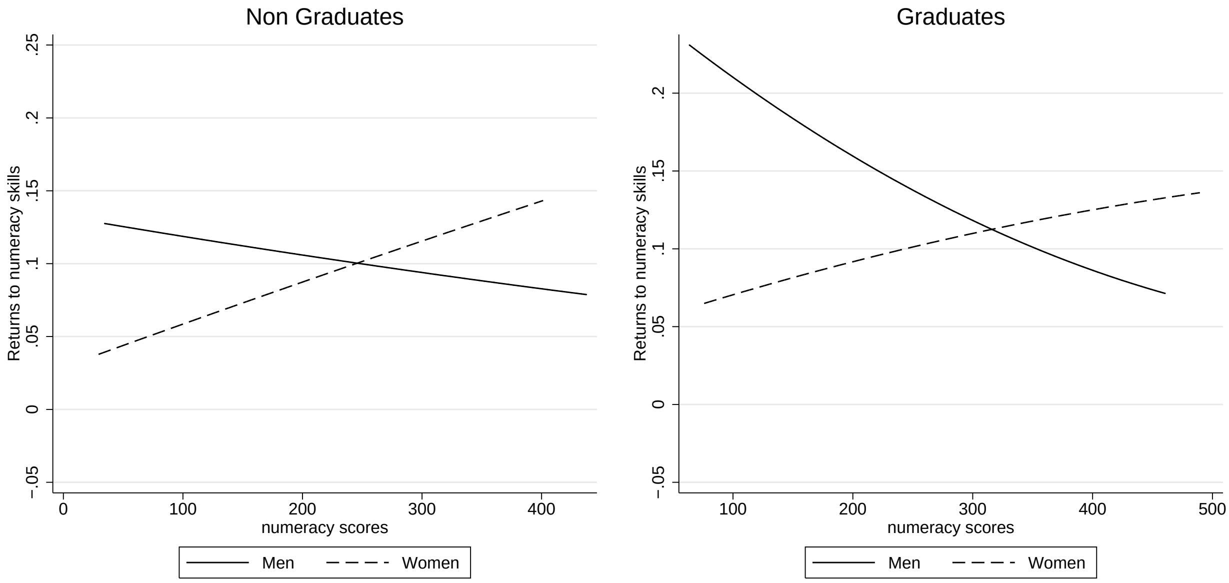
	All people		Graduates		Non Graduates		Graduates with STEM dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Numeracy	0.043***	0.043***	0.061***	0.060***	0.044***	0.045***	0.056***	0.056***
	(0.008)	(0.008)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.013)
Literacy	0.029***	0.029***	0.037***	0.036***	0.032***	0.033***	0.040***	0.039***
	(0.008)	(0.008)	(0.013)	(0.014)	(0.011)	(0.011)	(0.013)	(0.014)
Literacy*Numeracy	0.006**	0.006*	-0.002	-0.000	0.009**	0.011**	-0.002	-0.000
	(0.003)	(0.003)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
Fem*Num	0.002	0.003	-0.004	-0.002	0.004	0.002	0.003	0.005
	(0.011)	(0.011)	(0.016)	(0.017)	(0.015)	(0.016)	(0.017)	(0.017)
Fem*Lit	0.002	0.002	0.012	0.014	-0.013	-0.014	0.008	0.010
	(0.011)	(0.011)	(0.017)	(0.017)	(0.015)	(0.015)	(0.017)	(0.017)
Fem*Num*Lit		-0.002		-0.005		-0.006		-0.004
		(0.006)		(0.009)		(0.007)		(0.009)
STEM							0.035***	0.035***
							(0.013)	(0.013)
Female*STEM							-0.049**	-0.049**
							(0.020)	(0.020)
Female	-0.172***	-0.171***	-0.151***	-0.149***	-0.203***	-0.200***	-0.136***	-0.134***
	(0.007)	(0.008)	(0.012)	(0.012)	(0.010)	(0.011)	(0.013)	(0.013)
P(Literacy*Numeracy + Fem*Num*Lit)=0		0.3513		0.4346		0.3410		0.4737
Country, Occupation and Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	24252	24252	12341	12341	11911	11911	12341	12341

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models include only full-time workers and sample weights.
All models control additionally for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), and a constant.
Models (1) and (2) controls additionally for years of education.

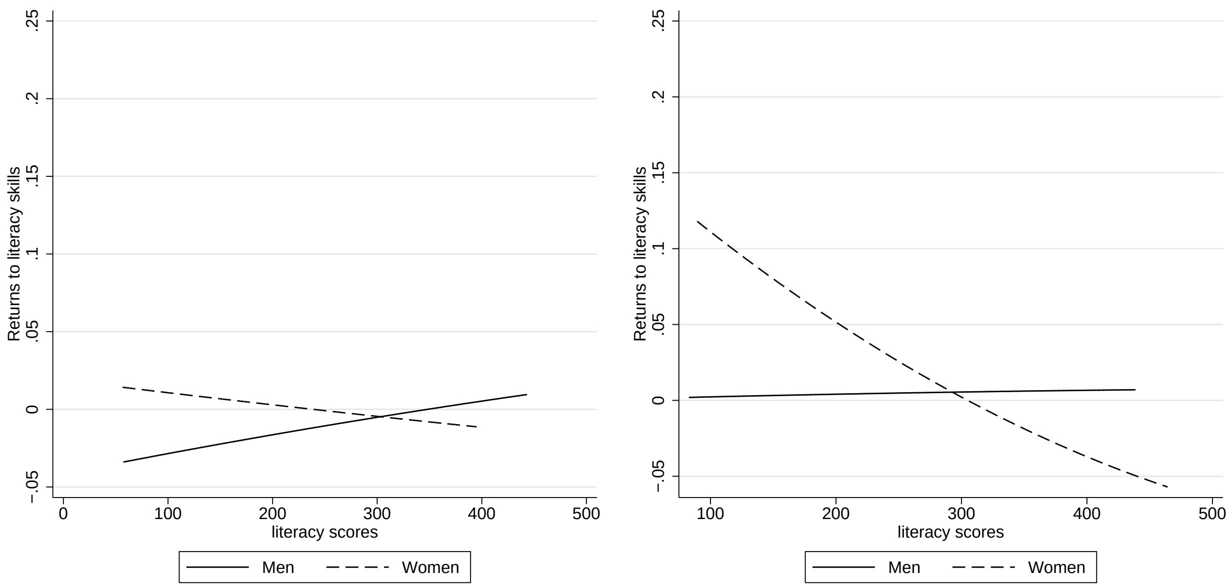
Table A4: Non linearities in numeracy and literacy skills (with more control variables)

	Total			Graduates			Non-Graduates		
	All	Men	Women	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numeracy	0.095***	0.068***	0.067***	0.120***	0.103***	0.082***	0.102***	0.075***	0.087***
	(0.004)	(0.006)	(0.006)	(0.008)	(0.013)	(0.010)	(0.006)	(0.007)	(0.009)
Literacy	0.004	0.023***	0.021***	0.022***	0.038***	0.045***	0.006	0.021***	0.020**
	(0.004)	(0.006)	(0.006)	(0.008)	(0.012)	(0.010)	(0.006)	(0.007)	(0.009)
$Numeracy^2$	0.010***	0.004	0.015***	0.003	-0.008	0.011*	0.005*	-0.000	0.011**
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)
$Literacy^2$	0.006**	0.008**	-0.000	-0.002	0.005	-0.012*	0.006**	0.007*	0.000
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.003)	(0.004)	(0.005)
Observations	67686	36279	31407	29944	14229	15715	38171	22308	15863
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Dependent variable: log gross hourly wage.
All models consider only full-time workers and basic specifications. Control variables include experience, experience squared, partner status and parental background, country dummies, and a constant for all models. Additionally, education is included in models (1), (2), and (3).

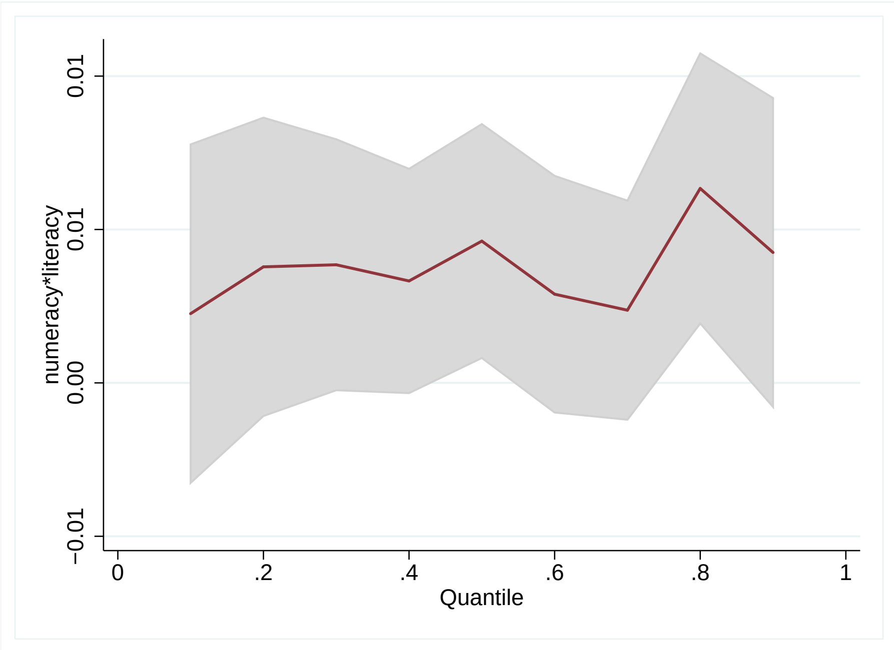


(a) Estimated marginal returns to numeracy skills

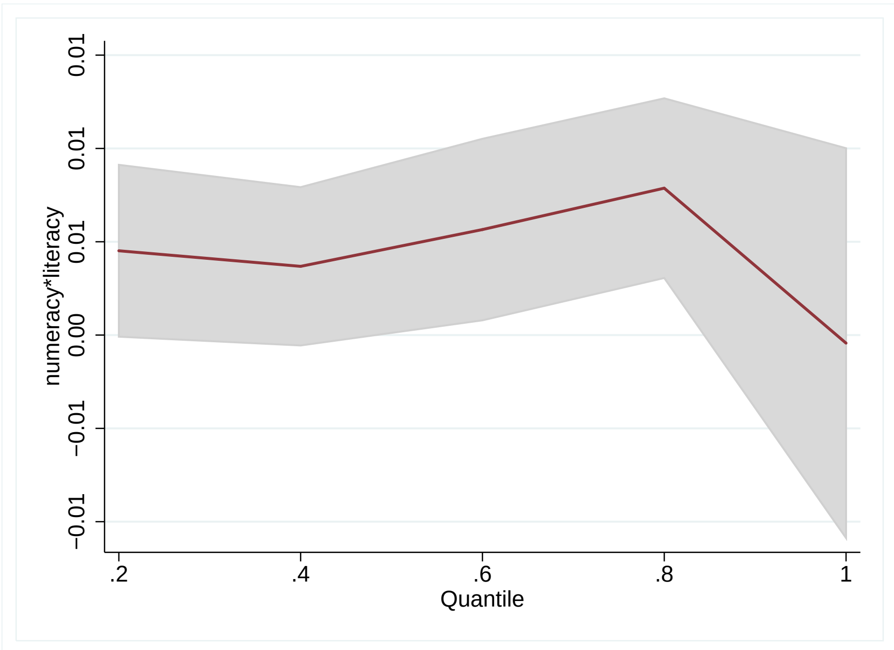


(b) Estimated marginal returns to literacy skills

Figure A2: Marginal returns to numeracy and literacy skills
Notes: Source: PIAAC. Based on non linear estimations that include numeracy, literacy, numeracy squared, literacy squared, education, experience, experience squared, and country dummies. Estimations are carried out for men and women separately as well as for graduates and non-graduates.



(a) Men



(b) Women

Figure A3: Quantile estimated returns to *Numeracy*Literacy* by gender for non-graduates
Notes: Solid lines connect the fitted estimates of *numeracy*literacy* skills across the wage distribution. Shadow areas show the 95% CI.

Table A5: Quantile effects by gender

	Men										
	Pooled	τ_u=0.10	τ_u=0.20	τ_u=0.30	τ_u=0.40	τ_u=0.50	τ_u=0.60	τ_u=0.70	τ_u=0.80	τ_u=0.90	τ_u=1
Numeracy	-0.001	0.044*	0.056***	0.058***	0.065***	0.063***	0.069***	0.065***	0.069***	0.062***	0.057***
	(0.010)	(0.022)	(0.013)	(0.013)	(0.012)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Literacy	0.005	0.025	0.014	0.011	0.011	0.017	0.013	0.016	0.015	0.020*	0.024**
	(0.009)	(0.021)	(0.013)	(0.013)	(0.012)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Num*Lit	0.005	-0.001	0.008	0.004	0.003	0.003	0.002	-0.000	-0.001	-0.000	0.002
	(0.004)	(0.009)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Education	0.007**	0.020***	0.029***	0.034***	0.036***	0.035***	0.038***	0.038***	0.040***	0.042***	0.044***
	(0.002)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	Women										
	Pooled	τ_u=0.10	τ_u=0.20	τ_u=0.30	τ_u=0.40	τ_u=0.50	τ_u=0.60	τ_u=0.70	τ_u=0.80	τ_u=0.90	τ_u=1
Numeracy	-0.005	0.031**	0.048***	0.058***	0.053***	0.051***	0.052***	0.057***	0.057***	0.055***	0.048***
	(0.009)	(0.012)	(0.011)	(0.013)	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.007)	(0.006)
Literacy	-0.002	-0.002	0.001	0.004	0.014	0.017	0.016***	0.014	0.013*	0.015*	0.022**
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.004)	(0.007)	(0.006)	(0.007)	(0.007)
Num*Lit	-0.005	-0.000	-0.003	-0.002	-0.003	-0.002	-0.001	-0.001	-0.002	-0.002	-0.002
	(0.003)	(0.008)	(0.007)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Education	0.004	0.010**	0.021***	0.029***	0.033***	0.036***	0.038***	0.040***	0.040***	0.041***	0.043***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Regressions control for education experience, experience squared. Models for total people control additionally for years of education.

Table A6: Returns to literacy and numeracy around the world (Total sample)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Female	−.188***	−.091***	−.066***	−.182***	−.181***	−.145***	−.079***	−.402***	−.225***	−.049**	−.259***
	(.006)	(.021)	(.023)	(.017)	(.036)	(.034)	(.016)	(.026)	(.015)	(.021)	(.044)
Numeracy	.050***	.066***	.059***	.112***	.011	−.065**	−.009	.168***	.049**	.057***	.024
	(.006)	(.017)	(.022)	(.020)	(.033)	(.027)	(.019)	(.033)	(.021)	(.021)	(.037)
Literacy	.024***	.064***	−.008	.038**	.020	.083***	.064***	−.071**	.018	−.017	.059
	(.006)	(.017)	(.022)	(.019)	(.027)	(.027)	(.020)	(.034)	(.022)	(.019)	(.037)
Literacy*Numeracy	.010***	.015***	−.012	−.020***	.018	.031*	.007	.013	−.003	.016*	−.005
	(.002)	(.004)	(.009)	(.007)	(.016)	(.017)	(.007)	(.015)	(.009)	(.010)	(.013)
Fem*Num	.004	.011	−.010	−.060**	.022	.151***	.029	−.075*	.043	−.019	.014
	(.009)	(.032)	(.030)	(.029)	(.044)	(.048)	(.024)	(.039)	(.027)	(.031)	(.060)
Fem*Lit	.007	−.031	.019	.061**	.014	−.142***	−.032	.083**	−.028	.049	.008
	(.009)	(.029)	(.031)	(.027)	(.040)	(.048)	(.024)	(.039)	(.027)	(.031)	(.054)
Fem*Num*Lit	.005	−.019*	−.012	.034***	−.020	−.048*	−.002	.019	.008	−.024*	.017
	(.004)	(.011)	(.017)	(.011)	(.021)	(.029)	(.009)	(.018)	(.011)	(.013)	(.027)
R^2	.973	.316	.422	.302	.483	.426	.413	.310	.446	.490	.390
Observations	42690	2080	1314	7888	1100	1429	2760	2392	1884	1546	1485
	Ireland	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.
Female	−.018	−.116***	−.311***	−.243***	−.063*	−.103***	−.194***	−.220***	−.110**	−.078***	−.112***
	(.044)	(.042)	(.039)	(.039)	(.033)	(.016)	(.039)	(.034)	(.047)	(.015)	(.038)
Numeracy	.127***	.075**	.064**	.101***	.002	.056**	.041	.037	.079	.002	−.013
	(.045)	(.035)	(.030)	(.036)	(.029)	(.023)	(.034)	(.037)	(.055)	(.019)	(.034)
Literacy	−.046	.025	−.023	−.001	.066**	.015	.038	.047	−.025	.056***	.108***
	(.051)	(.037)	(.030)	(.038)	(.030)	(.024)	(.032)	(.036)	(.052)	(.018)	(.036)
Literacy*Numeracy	.008	−.007	.010	.001	.000	−.010*	.020	−.025	.025	−.002	.027*
	(.013)	(.015)	(.012)	(.012)	(.011)	(.006)	(.014)	(.021)	(.032)	(.006)	(.015)
Fem*Num	−.083	−.053	.018	−.080	.061	−.010	.026	.026	−.016	.009	.044
	(.072)	(.054)	(.048)	(.054)	(.050)	(.031)	(.045)	(.046)	(.074)	(.024)	(.048)
Fem*Lit	.079	.010	−.000	.032	−.048	−.030	−.046	−.068	.053	−.030	−.050
	(.072)	(.053)	(.048)	(.053)	(.052)	(.030)	(.043)	(.045)	(.068)	(.024)	(.051)
Fem*Num*Lit	.007	.008	−.034	.027	−.014	.007	−.002	.048*	−.017	.009	−.007
	(.029)	(.021)	(.022)	(.021)	(.029)	(.010)	(.022)	(.026)	(.038)	(.009)	(.022)
R^2	.453	.500	.502	.514	.441	.438	.500	.396	.527	.513	.470
Observations	764	619	1405	1439	928	1968	1248	1556	808	1626	1618

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time workers (Canada includes part-time workers) Additional control for education, experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), and a constant. Numeracy and literacy scores standardized to std.dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country. Robust standard errors.

Table A7: Returns to literacy and numeracy around the world (Graduates)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Female	−.166***	−.029	−.078*	−.145***	−.161***	−.224**	−.105***	−.292***	−.226***	−.017	−.288***
	(.010)	(.044)	(.042)	(.023)	(.054)	(.110)	(.025)	(.040)	(.025)	(.039)	(.074)
Numeracy	.062***	.065*	.055	.132***	.029	−.111	−.009	.160***	.078**	.087**	−.018
	(.011)	(.034)	(.041)	(.025)	(.045)	(.096)	(.031)	(.051)	(.031)	(.042)	(.060)
Literacy	.042***	.063*	.039	.072***	.034	.106	.094***	.037	−.019	−.013	.154**
	(.011)	(.033)	(.045)	(.024)	(.041)	(.090)	(.032)	(.052)	(.038)	(.039)	(.060)
Literacy*Numeracy	.001	.020***	−.041	−.030***	.014	.010	.009	.005	.021	.005	−.038*
	(.005)	(.007)	(.030)	(.011)	(.024)	(.048)	(.010)	(.023)	(.024)	(.022)	(.020)
Fem*Num	.009	−.112**	−.009	−.076**	−.014	.193	.039	−.071	.069*	−.058	.157
	(.014)	(.054)	(.055)	(.036)	(.061)	(.121)	(.035)	(.058)	(.039)	(.054)	(.100)
Fem*Lit	.003	.051	.021	.059*	.051	−.120	−.055	.017	.010	.051	−.111
	(.014)	(.051)	(.057)	(.035)	(.057)	(.110)	(.037)	(.059)	(.043)	(.052)	(.081)
Fem*Num*Lit	−.002	−.070*	.002	.042***	−.020	−.100	.007	.021	−.024	−.013	.006
	(.008)	(.036)	(.040)	(.015)	(.032)	(.067)	(.014)	(.027)	(.026)	(.028)	(.066)
R^2	.972	.196	.324	.212	.453	.512	.369	.237	.283	.462	.379
Observations	18968	610	666	4677	571	335	1567	1187	1129	719	681
	Ireland	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.
Female	−.086	−.197**	−.249***	−.197***	−.106**	−.111***	−.164**	−.205***	−.079	−.110***	−.065
	(.056)	(.099)	(.058)	(.055)	(.045)	(.024)	(.064)	(.068)	(.076)	(.025)	(.055)
Numeracy	.090	.094	.052	.081*	.005	.044	.101	−.048	.127	.006	−.056
	(.065)	(.083)	(.042)	(.046)	(.040)	(.032)	(.067)	(.082)	(.092)	(.031)	(.056)
Literacy	−.047	.065	.006	.075	.071*	.040	.027	.065	.050	.025	.122**
	(.077)	(.096)	(.043)	(.055)	(.042)	(.032)	(.078)	(.078)	(.078)	(.032)	(.062)
Literacy*Numeracy	.020	−.036	.009	−.020	−.010	−.018**	.024	.069	−.036	.000	.025
	(.030)	(.050)	(.022)	(.027)	(.023)	(.007)	(.043)	(.071)	(.061)	(.010)	(.032)
Fem*Num	−.060	.074	.100	−.013	.028	.002	.037	.189**	−.125	.007	.082
	(.092)	(.110)	(.063)	(.077)	(.081)	(.041)	(.084)	(.095)	(.109)	(.038)	(.068)
Fem*Lit	.119	−.100	−.081	−.007	−.028	−.048	−.126	−.140	.044	.008	−.059
	(.098)	(.128)	(.065)	(.079)	(.077)	(.038)	(.091)	(.098)	(.097)	(.039)	(.074)
Fem*Num*Lit	.010	.039	−.041	−.051	.014	.015	.034	−.036	.040	.011	−.035
	(.048)	(.085)	(.033)	(.051)	(.043)	(.017)	(.050)	(.082)	(.066)	(.013)	(.041)
R^2	.399	.546	.493	.443	.379	.380	.429	.370	.440	.517	.448
Observations	567	154	789	760	493	1062	417	342	537	768	864

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time graduates (Canada includes part-time workers) Additional control for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), and a constant. Numeracy and literacy scores standardized to std.dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country. Robust standard errors.

Table A8: Returns to literacy and numeracy around the world (Non-Graduates)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Female	−.206***	−.106***	−.054	−.244***	−.226***	−.134***	−.056**	−.467***	−.241***	−.054**	−.240***
	(.007)	(.024)	(.033)	(.026)	(.055)	(.037)	(.023)	(.035)	(.021)	(.026)	(.058)
Numeracy	.061***	.072***	.098***	.092**	−.011	−.039	−.007	.225***	.045	.054**	.084*
	(.008)	(.020)	(.029)	(.037)	(.053)	(.026)	(.025)	(.044)	(.034)	(.026)	(.046)
Literacy	.017**	.079***	−.032	.037	.018	.083***	.041*	−.131***	.057*	−.013	.007
	(.008)	(.020)	(.029)	(.035)	(.041)	(.025)	(.024)	(.043)	(.031)	(.023)	(.045)
Literacy*Numeracy	.006**	.022***	.016	−.015	.011	.050***	.003	.013	−.003	.023	.016
	(.003)	(.005)	(.014)	(.017)	(.027)	(.017)	(.010)	(.023)	(.008)	(.015)	(.022)
Fem*Num	−.006	.071*	−.031	−.059	.070	.145***	.027	−.128**	.012	.016	−.098
	(.012)	(.040)	(.042)	(.052)	(.066)	(.054)	(.034)	(.054)	(.045)	(.043)	(.076)
Fem*Lit	.004	−.075**	.038	.022	−.043	−.104**	−.013	.102**	−.037	.023	.093
	(.012)	(.037)	(.043)	(.046)	(.060)	(.049)	(.034)	(.052)	(.043)	(.041)	(.070)
Fem*Num*Lit	.003	−.006	−.024	.018	−.013	−.027	−.007	−.003	.017	−.023	.001
	(.005)	(.014)	(.027)	(.021)	(.037)	(.026)	(.015)	(.030)	(.013)	(.021)	(.039)
R^2	.974	.227	.367	.239	.455	.355	.324	.292	.295	.393	.301
Observations	23905	1470	648	3211	529	1094	1193	1205	755	827	804
	Ireland	**Italy**	**Japan**	**Korea**	**Netherl.**	**Norway**	**Poland**	**Slovak R.**	**Spain**	**Sweden**	**U.K.**
Female	.111	−.086*	−.376***	−.307***	−.079*	−.126***	−.196***	−.241***	−.167**	−.073***	−.208***
	(.081)	(.050)	(.057)	(.059)	(.047)	(.023)	(.056)	(.041)	(.073)	(.020)	(.052)
Numeracy	.069	.073*	.097**	.114**	.011	.069**	.025	.048	.033	−.001	.027
	(.064)	(.039)	(.049)	(.058)	(.043)	(.034)	(.041)	(.044)	(.082)	(.024)	(.044)
Literacy	.000	.016	−.038	−.068	.063	.000	.044	.039	.006	.072***	.084*
	(.071)	(.041)	(.047)	(.060)	(.042)	(.035)	(.038)	(.042)	(.087)	(.023)	(.045)
Literacy*Numeracy	.015	.000	.021	−.021	−.009	−.006	.000	−.039*	.063	−.000	.042**
	(.024)	(.016)	(.019)	(.024)	(.015)	(.010)	(.019)	(.023)	(.052)	(.010)	(.018)
Fem*Num	.003	−.091	−.083	−.112	.024	−.027	−.043	−.007	.125	.020	−.023
	(.142)	(.065)	(.078)	(.079)	(.067)	(.047)	(.053)	(.054)	(.117)	(.033)	(.073)
Fem*Lit	−.080	.044	.040	.129	−.064	−.021	−.004	−.045	−.060	−.047	.023
	(.117)	(.061)	(.078)	(.080)	(.067)	(.046)	(.053)	(.053)	(.113)	(.033)	(.075)
Fem*Num*Lit	−.078	−.007	−.055	.068**	−.055	.004	−.032	.047	−.007	.010	.013
	(.069)	(.022)	(.040)	(.034)	(.038)	(.016)	(.028)	(.031)	(.076)	(.015)	(.032)
R^2	.481	.449	.419	.417	.331	.376	.327	.295	.526	.460	.445
Observations	197	465	616	679	435	906	831	1214	271	858	754

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time non-graduates (Canada includes part-time workers) Additional control for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), and a constant. Numeracy and literacy scores standardized to std.dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country. Robust standard errors.

Table A9: Returns to literacy and numeracy around the world (FEMALE Non-Graduates)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Numeracy	.062***	.115***	.044*	.010	.081**	.122***	.047**	.075***	.054**	.035	.097
	(.009)	(.024)	(.026)	(.025)	(.041)	(.035)	(.024)	(.028)	(.024)	(.027)	(.060)
Literacy	.014*	−.001	.020	.073***	−.050	−.010	.014	.016	.030	.034	−.012
	(.008)	(.021)	(.027)	(.022)	(.043)	(.034)	(.022)	(.026)	(.025)	(.026)	(.049)
Literacy*Numeracy	.009**	.014	.008	.003	−.008	.033**	−.003	.017	.015*	−.005	.009
	(.003)	(.011)	(.018)	(.009)	(.018)	(.016)	(.010)	(.014)	(.009)	(.013)	(.023)
R^2	.975	.244	.501	.264	.433	.351	.470	.033	.164	.358	.306
Observations	13574	862	351	2989	342	777	631	854	464	575	575

	Ireland	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.
Numeracy	.036	−.014	.042	.009	.059	.045	.018	.082***	.124*	.009	−.012
	(.111)	(.039)	(.045)	(.043)	(.039)	(.035)	(.025)	(.031)	(.067)	(.020)	(.036)
Literacy	.049	.066**	.017	.050	−.025	.001	.049*	−.020	−.045	.032	.106***
	(.123)	(.033)	(.043)	(.042)	(.038)	(.033)	(.026)	(.029)	(.059)	(.021)	(.037)
Literacy*Numeracy	.038	−.007	−.015	.012	−.000	.012	.007	.020	.042	.004	.023
	(.048)	(.013)	(.020)	(.016)	(.019)	(.010)	(.011)	(.019)	(.032)	(.011)	(.017)
R^2	.590	.338	.252	.330	.477	.369	.442	.288	.464	.410	.469
Observations	137	389	415	449	231	476	751	780	206	554	699

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time female non-graduates (Canada includes part-time workers) Control for experience, experience squared, occupational dummies and a constant. Numeracy and literacy scores standardized to std.dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country. Robust standard errors.

Table A10: Returns to literacy and numeracy around the world (STEM Graduates)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Female	–.198***	–.305	–.025	–.179***	–.199	–.443*	–.168***	–.510***	–.131**	.094	–.451***
	(.022)	(.298)	(.087)	(.055)	(.127)	(.243)	(.056)	(.062)	(.054)	(.094)	(.109)
Numeracy	.055***	–.009	.069	.176***	–.030	–.040	–.024	.156**	–.017	.057	–.045
	(.016)	(.046)	(.057)	(.031)	(.120)	(.111)	(.040)	(.068)	(.033)	(.063)	(.082)
Literacy	.045***	.094*	.167***	.031	.068	.046	.087**	–.062	–.011	–.049	.156*
	(.016)	(.051)	(.060)	(.029)	(.119)	(.206)	(.043)	(.070)	(.032)	(.057)	(.090)
Literacy*Numeracy	.006	.006	–.108***	–.015	.024	–.058	–.002	.027	.047***	.036	–.040
	(.007)	(.008)	(.036)	(.012)	(.055)	(.079)	(.011)	(.024)	(.010)	(.037)	(.037)
Fem*Num	.011	–.046	–.044	–.227***	.280	–.484**	.097	–.014	.014	–.094	–.028
	(.031)	(.509)	(.118)	(.080)	(.169)	(.211)	(.084)	(.095)	(.090)	(.127)	(.171)
Fem*Lit	.028	–.003	–.143	.145*	–.062	.216	.061	.084	–.006	.053	.113
	(.030)	(.475)	(.129)	(.085)	(.187)	(.204)	(.088)	(.095)	(.084)	(.101)	(.146)
Fem*Num*Lit	–.017	–.054	.102	.101**	–.095	.190	–.071	.036	–.036	–.056	–.039
	(.015)	(.167)	(.102)	(.039)	(.091)	(.157)	(.049)	(.035)	(.043)	(.061)	(.090)
R^2	.974	.368	.506	.266	.516	.684	.511	.390	.279	.503	.436
Observations	5697	206	206	1334	129	111	383	384	342	241	296

	Ireland	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.
Female	.095	–.361	–.211	–.201*	.159	–.174**	–.094	–.037	.019	–.151*	–.079
	(.170)	(.259)	(.143)	(.103)	(.134)	(.070)	(.122)	(.174)	(.158)	(.083)	(.143)
Numeracy	.068	–.063	.052	.102	–.027	.004	.167	–.055	.340**	–.067	–.048
	(.132)	(.234)	(.065)	(.062)	(.069)	(.064)	(.110)	(.148)	(.132)	(.044)	(.087)
Literacy	–.116	.088	–.048	.056	.191**	.097	–.006	.208	–.036	.076	.012
	(.142)	(.196)	(.080)	(.081)	(.074)	(.062)	(.118)	(.149)	(.106)	(.052)	(.086)
Literacy*Numeracy	.073	.081	.002	–.033	–.043	–.011	.007	.008	–.066	–.010	.059
	(.068)	(.127)	(.036)	(.052)	(.039)	(.015)	(.064)	(.132)	(.075)	(.016)	(.053)
Fem*Num	–.140	–.187	.293	–.040	.354**	.018	–.166	.142	–.257	.026	.126
	(.196)	(.659)	(.191)	(.183)	(.145)	(.093)	(.170)	(.226)	(.232)	(.112)	(.165)
Fem*Lit	–.093	.113	.044	.131	–.900***	.100	–.004	–.367	.266	.049	.069
	(.227)	(.573)	(.198)	(.184)	(.228)	(.090)	(.156)	(.235)	(.216)	(.127)	(.135)
Fem*Num*Lit	.124	–.033	–.138	–.025	.071	–.077*	–.081	.054	–.053	.005	–.129*
	(.113)	(.201)	(.123)	(.091)	(.117)	(.040)	(.080)	(.178)	(.101)	(.026)	(.066)
R^2	.560	.857	.528	.473	.602	.284	.590	.376	.529	.546	.521
Observations	174	41	222	327	145	280	138	129	173	185	251

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time STEM graduates (Canada includes part-time workers) All models control additionally for experience, experience squared, employment status of the partner, parental background, and having small child (2 years old or younger), occupational dummies, and a constant. Numeracy and literacy scores standardized to std.dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country. Robust standard errors.

Table A11: Returns to literacy and numeracy around the world (STEM Interaction)

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany
Female	−.158***	−.051	−.072*	−.144***	−.169***	−.193*	−.085***	−.267***	−.192***	−.004	−.299***
	(.010)	(.043)	(.041)	(.027)	(.059)	(.106)	(.026)	(.052)	(.030)	(.039)	(.076)
Numeracy	.060***	.074**	.058	.132***	.050	−.130	−.015	.152***	.051*	.086**	−.009
	(.011)	(.035)	(.041)	(.026)	(.043)	(.092)	(.030)	(.051)	(.031)	(.043)	(.058)
Literacy	.046***	.055*	.047	.071***	.028	.091	.099***	.047	−.001	−.015	.145**
	(.011)	(.032)	(.044)	(.024)	(.040)	(.087)	(.032)	(.053)	(.038)	(.039)	(.058)
Literacy*Numeracy	.003	.024***	−.045	−.029***	.009	.024	.008	.013	.024	.006	−.033
	(.005)	(.007)	(.029)	(.011)	(.023)	(.047)	(.010)	(.022)	(.023)	(.021)	(.020)
Fem*Num	.014	−.126**	−.005	−.074**	−.026	.219*	.038	−.033	.097**	−.064	.186*
	(.015)	(.051)	(.055)	(.037)	(.059)	(.119)	(.035)	(.059)	(.039)	(.055)	(.098)
Fem*Lit	.001	.047	.006	.059	.058	−.105	−.057	−.004	−.007	.061	−.139*
	(.015)	(.047)	(.057)	(.036)	(.055)	(.110)	(.037)	(.060)	(.043)	(.053)	(.080)
Fem*Num*Lit	−.002	−.033	.008	.041***	−.013	−.108	.010	.016	−.025	−.016	.012
	(.008)	(.030)	(.040)	(.015)	(.032)	(.068)	(.013)	(.026)	(.025)	(.028)	(.065)
Female*STEM	−.041**	−.275***	−.049	−.021	.038	−.235*	−.018	−.206***	−.005	−.008	−.210**
	(.017)	(.097)	(.052)	(.048)	(.096)	(.139)	(.040)	(.067)	(.048)	(.054)	(.090)
STEM	.032***	−.091***	.092**	.002	−.016	.091	.116***	.002	.095***	.026	−.010
	(.011)	(.032)	(.036)	(.026)	(.061)	(.086)	(.028)	(.052)	(.030)	(.039)	(.060)
R^2	.972	.226	.313	.211	.445	.509	.382	.233	.275	.455	.371
Observations	18895	610	666	4677	571	335	1567	1187	1129	719	681
	Ireland	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.
Female	−.090	−.186*	−.315***	−.220***	−.090**	−.093***	−.148**	−.247***	−.104	−.119***	−.053
	(.057)	(.102)	(.057)	(.059)	(.044)	(.025)	(.073)	(.074)	(.071)	(.026)	(.058)
Numeracy	.104	.088	.036	.093*	.002	.041	.097	−.061	.127	.008	−.069
	(.065)	(.091)	(.044)	(.048)	(.041)	(.032)	(.066)	(.091)	(.089)	(.031)	(.060)
Literacy	−.043	.070	.013	.077	.078*	.043	.012	.023	.037	.025	.122*
	(.077)	(.104)	(.044)	(.054)	(.042)	(.032)	(.079)	(.083)	(.079)	(.032)	(.063)
Literacy*Numeracy	.017	−.032	.012	−.020	−.012	−.017**	.033	.117	−.032	−.001	.039
	(.031)	(.050)	(.023)	(.027)	(.023)	(.007)	(.045)	(.075)	(.061)	(.011)	(.033)
Fem*Num	−.080	.035	.106*	−.025	.033	−.003	.046	.182*	−.122	.005	.109
	(.092)	(.114)	(.063)	(.078)	(.080)	(.041)	(.084)	(.107)	(.105)	(.039)	(.071)
Fem*Lit	.121	−.088	−.079	.004	−.027	−.042	−.112	−.072	.054	.012	−.069
	(.099)	(.133)	(.064)	(.080)	(.076)	(.038)	(.093)	(.104)	(.097)	(.038)	(.075)
Fem*Num*Lit	.018	.064	−.044	−.034	.014	.009	.026	−.096	.032	.011	−.040
	(.048)	(.080)	(.033)	(.049)	(.042)	(.016)	(.051)	(.084)	(.065)	(.014)	(.042)
Female*STEM	.080	−.128	.068	.041	.029	−.014	−.138	.149	.080	.007	−.032
	(.094)	(.156)	(.118)	(.086)	(.109)	(.042)	(.095)	(.111)	(.090)	(.045)	(.106)
STEM	−.022	−.030	.059	−.072	.022	.074**	.023	.024	−.052	.056**	.025
	(.074)	(.105)	(.050)	(.049)	(.037)	(.030)	(.074)	(.083)	(.066)	(.028)	(.059)
R^2	.390	.526	.480	.432	.368	.383	.425	.356	.437	.512	.426
Observations	567	154	789	760	493	1062	417	342	537	768	864

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All additional notes from Table A10 apply here.

Table A12: Basic regressions (with STEM interaction)

	Graduates					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.134***	-0.134***	-0.133***	-0.134***	-0.129***	-0.130***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Fem*STEM	-0.024	-0.024	-0.035**	-0.036**	-0.034**	-0.034**
	(0.015)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)
STEM	0.034***	0.034***	0.036***	0.036***	0.024**	0.024**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Exp	0.020***	0.020***	0.017***	0.017***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Numeracy	0.097***	0.097***	0.068***	0.068***	0.061***	0.061***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Literacy	0.040***	0.040***	0.028***	0.028***	0.025***	0.026***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Num*Lit	-0.001	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)
Fem*Num	-0.004	-0.004	-0.001	-0.002	0.001	-0.000
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Fem*Lit	0.006	0.006	0.017	0.016	0.019	0.018
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Fem*Num*Lit		0.000		0.002		0.003
		(0.007)		(0.007)		(0.006)
Constant	2.503***	2.503***	2.592***	2.592***	2.531***	2.532***
	(0.014)	(0.014)	(0.107)	(0.107)	(0.110)	(0.110)
Observations	30,644	30,644	30,644	30,644	30,621	30,621
R-squared	0.960	0.960	0.964	0.964	0.965	0.965
Country FE	YES	YES	YES	YES	YES	YES
Occupation FE	NO	NO	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO	YES	YES

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time workers graduates (Canada includes part-time workers).

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