Returns to Skills and Tasks: Evidence from 22 Selected Countries

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Abstract

Extended PIAAC survey of adult skills in a large set of countries gives the opportunity to investigate how different labour markets value workers' cognitive skills and the tasks they perform in their job. I find initially that higher school attainment and numeracy skills are systematically associated with higher wages in all 22 countries, but their returns differ substantially. Intriguingly, the returns to schooling are lower than 10 percent. Among workers aged 16-65, a one-standard-deviation in numeracy skills from their mean leads to an average increase of gross hourly wage by 13 percentage points across countries, but this masks the substantial heterogeneity. Estimated returns to numeracy in the countries with the highest returns are twice as large as in the countries with the lowest returns, while the returns of the remaining countries vary between 10 and 14 percent. Different sub-groups reveal interesting patterns of returns to skill but the most intriguing is the heterogeneity of returns across different age groups. Namely, prime-age workers (35-54) have somewhat three times higher (13.5 percent) returns than the youth employees (4.2 percent) aged 16-24. After entering tasks indices in my model, the average returns to numeracy across countries decreases from 13 to 8.8 percent. A one-standard-deviation increase in frequency of analytical and interpersonal tasks raises gross hourly wages averaging by somewhat more than five percentage points, whereas physical tasks decrease earnings up to four percentage points. An identical change in tasks discretion augments hourly earnings on average by approximately three percentage points. Finally, I find that countries with stricter employment protection and larger employment share have systematically lower returns to numeracy skills.

Key words: Mincerian wage equation; Return to skills; Task-based approach; PIAAC; International comparison; Heterogeneity.

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1 Introduction

Quality and skill levels of labour force have gained ground as fundamental features of contemporary economies (e.g. Hanushek and Woessmann (2008)). Furthermore, economists tried to establish explicit causal links between skill endowments, job tasks and labour market earnings (e.g. Acemoglu and Autor (2011, chap. 12), Autor and Handel (2013)), but the extant empirical evidence focus mainly on workers in the United States due to the plethora of data that exists. Consequently, the findings on how different labour markets value skills and tasks performed during work are limited. New and updated international comparable data from the Programme for the International Assessment of Adult Competencies (PIAAC) gives the potential to researchers to investigate how different economies reward worker's cognitive skills and the tasks they perform in their profession. In my thesis, I study how different labour markets compensate skills and both frequency and intensity of job tasks by estimating the corresponding monetary returns across the entire labour force aged 16-65 for 22 selected countries from Public Use Files (PUF) of PIAAC data.

Contrary to the rates of return to schooling[1] across countries, the estimates for cognitive skills and tasks were based on a limited amount of databases related to early-career workers in the United States (Hanushek et al. (2013, 2017)). Another strategy that the literature uses to evaluate cognitive skills is through students' performance according to test scores. However, these studies neglect to follow the tested students into the labour market in order to assess precisely how the skills acquired from schooling contributed to their earnings. Estimates based on workers in the starting point of their working career may not be representative for older workers. Firstly, sometimes employers need time to fully observe the skill profiles of their workers and reward them properly (Altonji and Pierret (2001)). Secondly, earnings trajectories vary substantially with respect to age (Björklund (1993); Haider and Solon (2006)), especially if economies have experienced considerable technological evolution (Autor et al. (2003); Acemoglu and Autor (2011)) and economic transitions from a centrally planned to a market economy (Mertaugh and Hanushek (2005)).

The new and updated PIAAC dataset provides international comparable data on adult skills based on a harmonised survey (OECD (2013, 2016)) for 33 countries. Two rounds of the survey have been undertaken. The first round of PIAAC, administered to 24 countries between August 2011 and March 2012, while the second round administered to an additional nine countries between April 2014 and March 2015. PIAAC has quite a few advantages comparing to other existing international databases. At first, covers participants from 33 countries over their entire work life. Secondly, samples are sufficiency large for all the countries. Thirdly, it contains indices for frequency and intensity for both everyday and in-the-job tasks. Finally, it assesses

[1] "Return to schooling" is being used by the relevant literature to indicate the impact that one additional year of schooling has on labour market earnings (Heckman et al. (2006)). For extensive international comparison of returns to schooling see Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2013).

directly cognitive skills in three domains: i) literacy; ii) numeracy; and iii) problem-solving in technology-rich environments.

My study aims to contribute in four ways to the literature. At first, I compare the estimates that two different human capital models produce (i.e. schooling and direct skill measurements) and then I record the dynamics of returns to numeracy skills, explaining the variation in gross hourly earnings across 22 selected countries. Secondly, I document how the returns to skills vary across different sub-groups and samples. Thirdly, I augment my empirical model inserting tasks indices to examine whether tasks frequency and discretion explain the variation in labour market earnings and affect the average returns to numeracy across countries. Finally, I derive stylised facts how different labour market institutions and economies' characteristics influence overall returns to numeracy including indicators such as employment protections, public employment share, GDP per capita and productivity growth.

Initially, my results indicate that higher school attainment and numeracy skills are systematically associated with higher wages in all 22 countries, but the returns to schooling hardly reach 10 percent. Among workers aged 16-65, a one-standard-deviation in numeracy skills from their mean leads to an average increase of gross hourly wage by 13 percentage points across countries. Moreover, different sub-groups (e.g. full-time, private sector, female and immigrant workers) show marked heterogeneity in returns to skill, while the most striking is the heterogeneity of returns across different age groups. Indicatively, prime-age (35-54) workers quite consistently demonstrate somewhat three times higher (13.5 percent) returns than the youth employees (4.2 percent) for the pooled sample of all 22 countries. Another intriguing finding is that considerable heterogeneity in returns to numeracy exists across countries. Estimated returns to numeracy in the countries with the highest returns are approximately twice as large as the countries with the lowest ones.

After enriching my empirical model with tasks indices, the average returns to numeracy across countries decrease from 13 to 8.8 percent. Regarding job tasks returns, a one-standard-deviation increase in frequency of cognitive/analytical and interpersonal/influence tasks raises gross hourly wages by somewhat more than five percentage points, while a similar change in work tasks discretion induces a three percentage-points increase in earnings approximately. On the other hand, physical tasks tend to decrease earnings by four percentage points. Moreover, I check the robustness of my estimates in two ways. My estimates remain robust after adding additional controls and restricting my sample to approximate better the lifetime returns to both numeracy skills and tasks. At the last part of my analysis, I exploit the cross-country dimension that PIAAC survey provides in order to examine whether the returns to skills differ due to cross-country differences in labour market structure. My results indicate that countries with stricter employment protection and larger employment share have systematically lower returns to numeracy skills.

The structure of my study is as follows. Section 2 discusses the related literature. Section 3 presents the evolution of literature's conceptual framework and my empirical model. Section 4 introduces PIAAC data to the reader. Section 5 illustrates the heterogeneity of returns across different model specification, different countries and sub-groups. Section 6 augments my empirical model and presents estimated returns to skills and tasks including robustness checks. Section 7 derives stylised facts about the cross-country characteristics which have an impact on returns to numeracy skills. Section 8 concludes.

2 Related Literature

The analysis of skills and their impact on earnings has constituted a perpetual topic of interest since Adam Smith's "Wealth of Nations" which published in 1776. However, returns to investment in education based on human capital theory have been estimated since the late 1950s, pioneered by Mincer (1958), who firstly measures human capital and subsequently, estimates its impact on wage distribution. Jacob Mincer notices that the measurement of human capital is not a simple task. In other words, human capital may be a non-measurable variable. Mincer (1958) defines human capital as the level of abilities and skills of an individual. Moreover, Mincer (1970, 1974) identifies two types of investment in human capital. At first, investments in formal education ("general human capital"), represented by years of schooling. Secondly, investments during working lifetime ("specific human capital" or "on-the-job training"), measured by years of work experience. Furthermore, he analyses both the impact of the individual schooling, as well as the work experience, on the dynamics earning's distribution, associated with workers. At last, he finds that inequality in wages augments with schooling level, age[2] and occupational hierarchy.

Mincer's establishment is widely approved by researchers who try to establish a causal link between human capital and wages. The relevant literature[3] has investigated both the micro- and macro-economic contribution of education (or human capital in general). Krueger and Lindahl (2001) clarify the differences between these two types of literature. On the one hand, the micro labour literature focuses on the estimates of the monetary return to schooling and try to exploit natural experiments to gather data for worker's earnings and school attainment. On the other hand, the macro growth strand examines whether the level of schooling in a cross-section of countries is associated with economic growth.

Even though, a substantial part of the extant literature exclusively bases mainly its estimates on United States employees, much work has been done on the differences between rates of return to schooling across

[2]In this regard, fundamental is the contribution of Becker and Chiswick (1966) who firstly observe the dynamics of income distribution within generations, while they enlist various determinants of investment in human capital such as inherited wealth (or parents' wealth), distribution of abilities, education opportunities and financial constraints.

[3]The book of Acemoglu and Autor (2011) provides a diligent review of education and human capital literature.

countries[4] (e.g. Psacharopoulos (1994), Psacharopoulos and Patrinos (2004)). One of the most interesting papers on that field is the one written by Montenegro and Patrinos (2013). Two aspects make this paper interesting. Firstly, the rich dataset of the World Bank which contains also panel data for various countries. Secondly, the strongest aspect of the paper is the comparability of its data by adjusting countries' surveys and their variables. To be precise, the authors secure the international comparability by defining in a uniform way the: i) dependent variable (i.e. hourly/weekly earnings); ii) control variables; iii) sample definition; and iv) empirical methodology for 131 different economies and 545 harmonized household surveys.

Mincer's insight is fundamental for both theoretical and empirical analysis; though this led researchers to measurement errors, ignoring that standard Mincer formulation assumes that schooling is the unique systematic source of differences in skills. Therefore, this suggests that the number of years of formal education alone is not a complete measure of skill and does not explain adequately the wage dispersion within education and other societal groups. There is an extensive strand of the literature-pioneered by Griliches (1977)-that examines potential endogeneity problems, omitted variable bias and various measurements errors of standard Mincerian equation. Therefore, the only way to establish a causal link between education and labour market earnings is by inserting education "as good as exogenous[5]".

Card (2001), in his influential paper, reviews a set of econometric studies (11 in number) that have attempted to measure the causal effect of education on labour market earnings by using institutional features of the "supply side[6]" of the education system as exogenous determinants of schooling. Reviewed papers have used mostly compulsory schooling laws, differences in the accessibility of schools as instrumental variables (IV, henceforth) for completed education. Their estimates unveil that the returns to schooling are systematically higher than the corresponding ordinary least squares (OLS, henceforth) estimates. However, Card (2001) reviews studies which focus solely on United States data. Similar findings can be found in the study by Trostel et al. (2002), who use strictly comparable cross-country (28 in number) panel data for the time period 1985-1995 from International Social Survey Program. Using spouses' and parents' schooling to instrument schooling, they show that conventional OLS estimates suggest a worldwide average rate of return to schooling

[4]See Badescu et al. (2011), Roszkowska (2014) and Pipien and Roszkowska (2015) for estimated returns to education across European countries.

[5]Angrist and Pischke (2014, chap. 6) discuss extensively how education can be inserted "as good as exogenous" in an empirical framework.

[6]Badescu et al. (2011) mention two types of instruments to model schooling or education "as good as exogenous". The first category of instruments associates to education system's structure, so-called "supply-side" instruments (e.g. school reforms, area of residence and distance from university), while the second category, so-called "demand-side", consists of respondent's family/household background characteristics. Even though the second set of instruments is preferred by economists, the authors argue that both types of instruments may violate the hypothesis of "exclusion restriction" and we cannot rely on instrumental variables to isolate the exogenous effect of education or schooling. For that reason, the authors propose another method to soothe endogeneity. Namely, endogeneity could be partly solved by including covariates to capture the unobserved heterogeneity which is included in the disturbance term.

of just under five percent for men and a little under six percent for women. The relevant IV estimates suggest that OLS estimates are biased downwards by about a percentage point or more.

Card (2001) enlists four potential reasons to justify this downward bias. The first explanation of this phenomenon-initially proposed by Griliches (1977)-is that ability biases[7] in the OLS estimates of the return to schooling are relatively small and the difference between the IV and OLS estimates reflect the downward bias in the OLS estimates attributable to measurement errors. A second explanation is that the IV estimates are upward biased than the corresponding OLS estimates by unobserved differences between the characteristics of the "treatment" and "control" groups implicit in the IV scheme. A third possibility is that researchers tend to favour those instruments that yield a higher t-statistic (i.e. ostensibly stronger instruments) for the estimated return to schooling. In the returns to education literature this is called "specification searching". The final plausible interpretation is that marginal returns to education among the low-education sub-groups typically affected by "supply-side" innovations tend to be relatively high, reflecting their high marginal costs of schooling, rather than low ability that limits their return to education.

Intriguingly, Card (2001) mentions that in many cases the IV estimates are relatively imprecise and none of the empirical strategies is based on true randomization. Thus, no individual study is likely to be decisive in the debate over the magnitude of ability biases in OLS estimates of the return to schooling[8].

Except the innate ability bias issues, attention has been given also to the differences in school quality[9]. Ignoring education quality could bias the estimated returns to schooling and may introduce persistent measurement errors. This is quite important especially when the analysis of returns to schooling is being performed across different countries. In other words, identical years of school attainment do not necessarily mean that individuals should expect the exact same returns. For instance, the return of an additional year of schooling might be higher in Finland than Greece because the first country, according to international standings, has one the best education systems throughout the world. Thus, Finnish schools equip their students with more advanced skills than the Greek counterparts and labour market reward these skills with higher returns. Differences in school quality can be found also within countries. Barro and Lee (2013) document that average years of schooling has been increased over time, while richer regions/municipalities may be in position to organise better curricula and hire more experienced teachers.

[7]Similar discussion can be also found in Card (1999), where he argues that individuals with higher innate ability and performance tend to systematically extend their school attainment. This usually leads to a considerable upward bias in the derived returns to schooling. Not to mention the reverse causality and that lies due to the fact that individuals extend their schooling because they initially observe that highly paid jobs are characterized by advanced levels of skills and schooling.

[8]Trostel et al. (2002), Badescu et al. (2011), Roszkowska (2014) and Pipien and Roszkowska (2015) reach to the same conclusion. In their opinion, IV estimates are associated with strong a priori assumptions and the outcomes might differ substantially according to the selected sets of instruments. It is worth mentioning that Pipien and Roszkowska (2015) they use an alternative method called Seemingly Unrelated Regression Equations (SURE) to address endogeity issues.

[9]See Hanushek and Zhang (2006) and their discussion about quality-adjusted years of schooling.

Another fact that has to be taken into consideration is that the estimated returns to schooling differ with respect to age. However, the classical Mincerian establishment is based on the assumption that the cross-sectional labour market earnings of a 50-year-old tertiary graduate is a sufficient approximation of what a 25-year-old tertiary graduate should expect in the future. The specific assumption using cross-sectional data is not entirely correct and the current earnings are not always in line with the expectations about the lifetime earnings. Björklund (1993) and Haider and Solon (2006) prove that current earnings constitute a good proxy for lifetime earnings when observed for individuals aged around 35 to 54 in Sweden and the United States, respectively.

Many scholars have recognised the crucial role of technology and its patterns. The rapid technological progress has affected considerably the structure of the labour markets and has changed the nature of many occupations. Jan Tinbergen was one of the first economists who realised this unique impact of technological advance on labour market's structure and worker's earnings through a relative labour supply and demand framework. Tinbergen (1974), in his seminal paper, illustrates that wage equality depends on the technological progress and on the "race" between the supply and demand of high educated/skilled workers. In addition, he introduces the so-called term "skill biased technology" which refers to the fact that technological development tends to complement or substitute specific type of employees and professions[10]. Katz and Murphy (1992) start an interesting discussion how technological progress and productivity patterns associate with the future returns to schooling and labour market earnings, while Goldin and Katz (1996) investigate, for the United States labour market, how technological progress affected relative demand for highly skilled workers in the past (1910-1940).

Therefore, it is profound that schooling from the extant literature, as a measure of individuals' human capital, suffers from a variety of issues which, by their turn, distort the estimated impact of increased skills (e.g. measured as an additional year of schooling) on worker's compensation. The "new economy" perspective suggests that the technological change has led to higher compensation for jobs requiring, for example, greater computer literacy, interpersonal and other cognitive skills.

For that reason, another strand of literature has been developed from the economists in order to ameliorate measurements errors and ability bias based on direct measures of cognitive and other skill domains[11]. Ingram and Neumann (2006) argue that education *per se* does not measure skill adequately and subsequently explain the alternative measure based on the observed skill characteristics of the job. After analysing the returns to various dimensions of skill, including formal education, they find that the return to years of education has been constant since 1970 for the United States labour market. At last, the authors underline that variations in direct measures of skill account for a considerable fraction of the increased income dispersion

[10] Extensive discussion for "skill biased technology" and "job polarisation" can be found in Autor et al. (2003).

[11] I describe in detail the conceptual framework behind the specific methodology in Subsection 3.1.

among the college educated and those who have not acquired college education.

The usage of the alternative skill approach keeps gaining ground and this trend is prominent from the relevant literature. Deming (2015) and Edin et al. (2017) highlight the role of both social (i.e. interactive or interpersonal) skills and analyse their contribution in wage equality and their impact on labour market rewards for the United States and Sweden, respectively.

Hanushek et al. (2013) study how different economies[12] evaluate cognitive skills. For their estimates, they use OECD PIAAC[13] data which include assessments of cognitive skills in three domains. Hanushek et al. (2013) find that one standard-deviation increase in numeracy skills is connected with an 18 percent wage increase on average among workers aged 35-54. However, there is marked heterogeneity across countries and returns vary from 12 to 28 percent. The lowest return belongs to Sweden and the highest one to the United States. Estimates remain robust for different earnings and skills measures, while they vary systematically across different sub-samples. Finally, countries with higher labour union participation, stringent employment protection legislation and larger public sector as percentage of labour force have relatively lower returns to skill.

At last, it is worth mentioning one more strand of the extant literature. This part of the literature established with the influential paper of Autor et al. (2003) who developed a task-based approach (i.e. the tasks performed in job) to study the link between evolving technology and shifts in the demand for workers of different educational and skill levels. Their primary hypothesis is that workplace computerization leads to the automation of a large set of "middle education" (i.e. high school or some college) routine cognitive and manual tasks, such as book-keeping, clerical work and repetitive production tasks. Job tasks in these occupations are easily codified because they follow strict and well-defined procedures, so-called "routines". Autor et al. (2003) using representative data on task input for 1960 to 1998 show that within industries, occupations and education groups, computerization is associated with reduced labour input of routine manual and increased labour input of non-routine cognitive tasks. Task shifts into education demand can explain up to 60 percent of the estimated relative demand shift favouring college labour during 1970 to 1998.

Autor and Handel (2013) try to expand both empirical and theoretical literature using job tasks as a pillar for conceptualising[14] and quantifying job skill demands. Their analysis makes three contributions. Firstly, they document that job tasks differ substantially within as well as between occupations. Secondly, they find that the tasks that workers perform on the job are sufficient predictors of hourly wages differentials between occupational, demographic and education groups. Finally, the paper offers a theoretical framework that creates causal links between human capital, different occupational tasks and the employees' earnings.

[12] To be precise, 22 countries participated in the first round of PIAAC data collection.

[13] I describe PIAAC data extensively in Section 4.

[14] Author's conceptual framework follows the definitions in Autor et al. (2003) for abstract, routine and manual tasks.

Namely, the framework follows a task-based Roy model in which workers possess a bundle of basic skills and occupations are characterized as a bundle of basic tasks[15].

3 Thesis Conceptual Framework and Empirical Methodology

The econometric literature has unveiled the multiple issues that arise from the estimation of a standard Mincerian model, as I describe in Section 2. Griliches (1977), in his influential work, started the causality debate around the Mincerian framework by noticing that the estimates are quite biased due to omitted and confounding influences. In addition, he underlies that by adding multiple covariates in order to explore the variation of human capital and workers' earnings is not a solution. This method results to noisy and erroneous estimates of returns to schooling. Hence, we have to abandon the monolithic concept of schooling to approximate human capital, especially when we examine wage distribution within a modern and technologically advanced economic setting.

3.1 Conceptual Framework

Human capital is an inert and multidimensional variable which makes it which makes sufficient measurement quite a challenging task. Many measurements techniques and databases suffer from errors and deficiencies (Hanushek and Woessmann (2009)). Gradually, labour economists orient their interest in the competencies of the population and the quality of the labour force. Skills constitute a fundamental aspect in advanced technologically environments (Ingram and Neumann (2006); Hanushek et al. (2017)). My empirical methodology is in line with an alternative approach which has its foundations on direct assessment of cognitive and other skills[16]. Before describing the direct skill measurement approach, it is worth checking how the conceptual framework evolved[17] in human capital literature and labour economics.

Numerous studies of labour market earnings use the standard Mincerian wage equation because it constitutes a stable benchmark for estimating wage differentials (Lemieux (2006)). Mincer's equation can be simply written as:

$$\log y_i = c + rS_i + \alpha_1 X_i + \alpha_2 X_i^2 + \epsilon_i \tag{1}$$

where y_i refers to individuals i earnings which are a function of schooling (S) and quadratic term of actual

[15] Yamaguchi (2016) constructs a similar model to examine how technology reduces wage inequality between men and women.

[16] The studies by Neal and Johnson (1996) and Murnane et al. (2000) preliminary built their empirical analysis on the specific alternative approach.

[17] Hanushek and Woessmann (2008) illustrate plainly the evolution of human capital models over time.

work experience (X). The disturbance term (ϵ) absorbs the idiosyncratic earnings differences. In general, the empirical literature usually presumes that the stochastic term is independent to S. Mincer's framework uses school attainment as a proxy of human capital because Mincer (1970, 1974) suggests that individuals initial incentive for schooling is to improve their general skill level. However, econometricians have already revealed the endogeneity issues and omissions around Mincerian formulation[18] (Card (1999, 2001)).

Furthermore, another strand of research tried to replace S in Eq. (1) and approximate human capital with the so-called "educational production functions". This branch of research conceives that other determinates of human capital (or skills) exists, besides school attainment. The "educational production functions" can be written simply as:

$$H = \kappa F + \rho Q(S) + \nu A + \delta X + v \tag{2}$$

where F represents family inputs (e.g. educational level, wealth), Q(S) is a function that entails both quantity and quality of schooling (S), A refers to individuals innate ability and X represents other control variables including work experience, health status, gender and other relevant parameters. Eq. (2) has been used to estimate school performance (or skills) in the place of H. However, "educational production function" is exposed to severe biases for two reasons[19]. Firstly, stochastic term (v) is hardly orthogonal with the determinants of Eq. (2). Secondly, individual ability (A) is hardly measurable and by omitting such variable we ignore the self-selection of more adept students to more schooling.

As I mentioned, I adopt the alternative empirical approach associated with direct measures of cognitive skills. This estimation technique considers harmonised assessment of literacy and numeracy performance[20]. These assessments are able to capture a considerable part of variation in H, as depicted in Eq. (2), because they take fully into consideration school quantity, individual ability and skills developed during working career (Hanushek et al. (2013, 2017)). Therefore, cognitive skills measures and ultimately their estimated rates of returns are preciser and more credible than school attainment.

Nevertheless, the direct skill measurement approach is still prone to measurement errors, while the issue of self-selection persists because extension of school attainment associates with more advanced cognitive skills (Cunha et al. (2006)). These are not the only flaws of the cognitive skill approach. Murnane et al. (2000) distinguishes between the direct return to observed cognitive skills and indirect returns of additional schooling and argue that even up to one-half of the aggregate return springs further school attainment. Deming (2015) underlines the importance of social skills and their potency to explain a considerable part of variation in workers' earnings particularly for women. This leads me to think that the direct empirical

[18]See discussion in Section 2.

[19]See Card (1999, 2001) and Angrist and Pischke (2014, chap. 6), especially their discussion about ability bias.

[20]These assessments are recently available for problem-solving skills. See OECD (2013, 2016).

analysis of cognitive skills may suffer from standard omitted variable bias because labour market rewards also non-cognitive skills. Hence, the causal link between labour market earnings is fragile and the estimated coefficients of cognitive skills should be interpreted cautiously.

3.2 Empirical Methodology

Taking into account the course of empirical conceptualisation, I derive my baseline estimates in Section 5 using an analogue model to a standard Mincerian wage equation replacing the main explanatory variable of school attainment with measured cognitive skills[21]. The algebraic form of my estimated wage equation is:

$$\log y_i = \alpha_0 + \alpha_1 C_i + \alpha_2 PE_i + \alpha_3 PE_i^2 + \alpha_4 G_i + \epsilon_i \tag{3}$$

where y_i refers to gross hourly earnings (in PPP U.S. dollars) of individual i, PE represents years of potential experience[22] (age minus years of schooling minus six), PE^2 is the squared years of potential experience divided by 100 for analytical purposes[23]. G is a binary gender indicator (i.e. 1 for females; 0 for males) and ϵ is an error term. G checks gross hourly earnings differences in levels between men and women. It is prudent to include gender control since males and females have different earnings trajectories because of sex discrimination and interruption of labour force participation due to maternity – meaning different coefficients for cognitive skills (C) and potential experience (PE) in the earnings function (see Oaxaca (1973); Psacharopoulos and Tzannatos (1992, p. 157)).

Eq. (3) is the simplest form of my estimated earnings equation. Because of the fact that PIAAC survey contains international comparable data, my empirical analysis has to take into account the different countries. Eq. (3) can be written as:

$$\log y_{ic} = \eta_c + \alpha_0 + \alpha_1 C_{ic} + \alpha_2 PE_{ic} + \alpha_3 PE_{ic}^2 + \alpha_4 G_{ic} + \epsilon_{ic} \tag{4}$$

where c indicates the country and η_c country-fixed effects should be included for pooled estimations. The parameter of interest is α_1 which is called "return to skill" by the relevant literature. I do not include other interesting control variables in order to avoid reverse causality and additional measurement issues. For instance, parents' education level might affect implicitly individuals earnings via their labour market connections (Card (2001)), while self-reported health status, represented as an ordinal variable (e.g. bad=0;

[21] To be precise, I use numeracy skills as measured in PIAAC survey to derive my estimations throughout my empirical analysis. In Sub-section 4.2, I describe in detail why numeracy skills is the most suitable variable to estimates the returns to cognitive skills.

[22] Actual work experience may be partly endogenous to skill levels (Hanushek et al. (2013)). That is the reason I use potential work experience.

[23] I do that in order to derive conciser estimated coefficients.

very good=4), is inappropriate because health perceptions differ substantially across and within countries. Another methodology is needed to create strictly comparable health perceptions via self-reported data (see Nattrass et al. (2007)). To be consistent in Sub-sections 5.2 to 5.4 , I derive my estimates separately for each sub-group I am interested in.

Finally, in Section 6 I enrich my empirical model including a few indicative tasks[24] performed in occupations. I follow the empirical sophistication of Autor and Handel (2013), who argue that workers choose occupations and job tasks with respect to their skill endowments in order to maximise their outcome and efficiency. In addition, according to Autor et al. (2003), job tasks are robust predictors because technological advance gradually alters the nature of many occupations. Thus, continuous technological progress in labour market alters skills requirements, the significance of job tasks and the criteria that the labour market follows to reward workers.

The job tasks[25] I include are the: i) cognitive/analytical (ICT); ii) influence/interpersonal (INFL); iii) physical/manual ($PHYS$). At last, I add tasks discretion ($DISC$) on the job. Eq. (4) becomes:

$$logy_{ic} = \eta_c + \alpha_0 + \alpha_1 C_{ic} + \alpha_2 PE_{ic} + \alpha_3 PE_{ic}^2 + \alpha_4 G_{ic} + \alpha_5 ICT_{ic} + \alpha_6 INFL_{ic} + \alpha_7 PHYS_{ic} + \alpha_8 DISC_{ic} + \epsilon_{ic} \quad (5)$$

I select to insert the aforementioned tasks in my empirical framework for various reasons. At first, computerization of the economies and continuous technological advance raise the role of cognitive/analytical (ICT) tasks, whereas physical ($PHYS$) tasks are characterised mostly by negative returns because they follow well-defined rules ("routines") which make them easily automated and performed mainly by less skilled/educated workers (Autor et al. (2003)). Secondly, interpersonal/influence ($INFL$) tasks frequency and skills have started to gain ground in labour economics. Interpersonal tasks are being performed mostly from managers or other positions which require to organise, guide or even coach a large groups of heterogeneous workers (see Deming (2015); Edin et al. (2017)). Finally, I use an index of task discretion ($DISC$) in order to control for the intensity of in-the-job tasks. In my opinion, this index is a necessary component of a task-based analysis because individuals across or even within the same occupation may perform more or less the same tasks but the intensity of tasks might differ substantially (e.g. analytical tasks performed by a programmer and an administrative assistant).

Except α_1, the coefficients of interest are also α_5, α_6, α_7 and α_8 of each task index added. These estimated coefficients usually called "returns to tasks" in the literature. However, the actual average "returns

[24] Acemoglu and Autor (2011, chap. 12) provide a diligent review of the task-based literature, while highlight the implications of technological advance on the labour market and the role of tasks which workers perform across occupations.

[25] For job tasks I extract data from PIAAC. Precise definitions and description of the selected tasks can be found in Sub-section 4.3.

to tasks" in Section 6 do not depict the average returns to tasks over all industries and occupations because of the self-selection (i.e. non-random assignment) of employees towards specific professions. In other words, efficient workers with high performance in the aforementioned tasks will choose occupations which highly reward those tasks.

4 OECD PIAAC Survey of Adults Skills

My main source of data is the Programme for the International Assessment of Adult Competencies (PIAAC, henceforth). Developed under the auspices of Organisation for Economic Co-operation and Development (OECD, henceforth) to provide international comparable data on adult skills[26] through a standardised survey (OECD (2013, 2016)). To date, two rounds of the survey have been undertaken. The first round of PIAAC, administered to 24 countries between August 2011 and March 2012, while the second round administered to an additional nine countries between April 2014 and March 2015. As a result, PIAAC survey contains comparable cognitive skill data for 33 countries.

The countries[27] participating in the first round were: Australia, Austria, Belgium, Canada, Cyprus[28], the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom and the United States. In Belgium, data was collected in the Flanders region only. In the United Kingdom, out of four devolved administrations only England and Northern Ireland took part. In the second round of adults skills survey, the participating countries[29] were: Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey. In Indonesia, data was collected only in the Jakarta municipal area. The final updated version of PIAAC released on June 28, 2016.

For my analysis I am able to use 22 out of 33 countries. Public Use File (PUF, henceforth) is the version of PIAAC data available for the public. The dependent variable of my empirical analysis, as depicted in its simplest form in Eq. (3), is the gross hourly workers' earnings. However, in the PUF, Australia, Austria, Canada, Germany, New Zealand, Sweden, Singapore, Turkey and the United States do not report the continuous data related to labour market earnings and age due to legal restrictions, while Indonesia

[26]Human capital literature defines "competency" and "skill" differently. On the other hand, in the context of the PIAAC competency and skill are not differentiated and these terms are used interchangeably. Accordingly, I will not distinguish the two terms.

[27]Cyprus and the Russian Federation are OECD partners and the remaining countries participates in the first round are OECD members.

[28]The information relates to the area under the effective control of the Government of the Republic of Cyprus.

[29]Indonesia, Lithuania and Singapore are OECD partners and the remaining countries participated in the second round are OECD members.

(Jakarta) does not publish the data at all. I exclude the sample of the Russian Federation it does not include the population of the Moscow municipal area. The data published, therefore, are not representative of the entire resident population aged 16-65 (OECD, 2016, p. 61). Effectively, my empirical analysis contains the samples of the following countries: 1) Belgium (Flanders), 2) Chile, 3) Cyprus, 4) the Czech Republic, 5) Denmark, 6) Estonia, 7) Finland, 8) France, 9) Greece, 10) Ireland, 11) Israel, 12) Italy, 13) Japan, 14) Korea, 15) Lithuania, 16) the Netherlands, 17) Norway, 18) Poland, 19) the Slovak Republic, 20) Slovenia, 21) Spain and 22) the United Kingdom (England & Northern Ireland).

4.1 Sample Design

The purpose of PIAAC is to measure the cognitive skills and work-related tasks needed for workers to excel in the labour market. Survey's target population[30] for the adults skills consisted of population aged 16-65 years residing in the country at the time of data collection, independently of nationality or citizenship. Respondents were interviewed at home in the language of country of residence. Countries' sampling frames were obliged to cover at least 95 percent of the target population following proper post-sampling weighting. Because of the fact that PIAAC are already weighted, I assign the same weights to each country throughout my empirical analysis.

Countries worked to reduce non-response bias to the greatest extent possible before, during and after data collection. Most countries followed the required sample monitoring activities and guidelines of OECD (2013) to reduce bias to the lowest level possible. Australia, Indonesia (Jakarta), Korea, Turkey and the United States achieved an overall response rate of 70 percent or greater. Cyprus and Ireland also achieved overall response rates of 70 percent or greater. The remaining countries achieved response rates lower than 70 percent.

4.2 Background Questionnaire and Skill Domains Assessment

Prior to skill assessment, all respondents replied in a background questionnaire that collected various information for participants related to labour market earnings, employment status, actual work experience[31], several tasks frequency, personal and parents' highest level of education and other demographic aspects. Respondents were able to seek assistance from others in the household (or in other area where the interview took place) in completing the questionnaire preciser. On the other hand, assistance from others in completing the cognitive assessment was forbidden. The key cognitive competencies-described rigorously in OECD

[30] OECD (2016, Table 3.8) shows the total samples of each country and provides information about the oversampled sub-groups which might distort their representativeness.

[31] Defined as the total number of years in which respondents spent at least six years in paid job.

(2013, 2016)-assessed on a 500-point scale were associated with three skills domains, stipulated as:

- *Literacy*: ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals and to develop one's knowledge and potential;
- *Numeracy*: ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
- *Problem solving in technology-rich environments*: ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.

Participating economies had the choice of assessing all three domains or literacy and numeracy skills only. The counties, included in my dataset, that did not assess the third skill domain were[32]: Cyprus, France, Italy and Spain. For my analysis, I use solely numeracy scores as the main explanatory variable to approximate cognitive skills (C), as modelled in Eq. (3). More specifically, I do not use problem-solving scores to circumvent losing a considerable amount of observations. Additionally, numeracy and literacy (problem-solving) are strongly-correlated with an individual-level correlation of around 0.84 (0.72). I favour numeracy over literacy skills because literacy assessment has a considerable drawback. Namely, poor performance in the literacy assessment among non-natives such as immigrants and their children, is not necessarily indicative of poor performance. In other words, low literacy in the language of country of residence does not indicate that they lack proficiency in their native language. For instance, a Turkish immigrant in France may depict poor skills in French language tests but he/she may be a quite competent reader when being evaluated in his native language (in Turkish). All things considered, numeracy skill scores seem the most comparable variable across different countries. At last, for analytical purposes and easier interpretation of the following wage regressions, I standardise the corresponding scores to have within-country mean of zero and within-country standard deviation of one.

4.3 Tasks Indices Measurement

PIAAC dataset contains data for specific tasks, performed by workers, organised in various clusters. Interestingly, PIAAC includes data for both in-the-job and everyday tasks. However, I focus on selected work tasks which they constitute good proxies for cognitive, interpersonal and manual tasks. In addition, PIAAC provides an index for the intensity of tasks performed in work. Data for work tasks were collected from both currently employed respondents and from those who were employed in the previous 12 months before the

[32] Indonesia chose also not to assess problem solving in technology-rich environments.

time of the interview. As OECD (2016, pp. 40-42) describes, the collected information about work tasks took into account five specific factors. Namely, these factors were:

1. *incidence*: whether or not a given task/activity is performed;
2. *variety*: the diversity of tasks or activities that are performed or undertaken;
3. *frequency*: the frequency with which a given task or activity is performed or undertaken;
4. *complexity*: the level of cognitive demand or competency required to perform the task/activity successfully;
5. *criticality*: the importance of the task or activity to the performance of the job

To be precise, 12 tasks indices were calculated within PIAAC framework[33]. Five out of 12 task indicators were derived from a unique item of the background questionnaire. Namely, these tasks measures were problem solving, co-operative, self-organising, physical tasks and dexterity. These direct measures take five possible values, ranging from zero ("never performing the corresponding task"), to four ("perform the specific task every day"). However, this simplistic indication of tasks frequency does not affect considerably my analysis because I am using only the index related to physical tasks. The remaining tasks indices (seven out of 12) are continuous variables ranging from zero to four, representing the level of performing the underlying tasks based on the aforementioned criteria. For simplicity reasons OECD (2013, 2016) interprets the specific variables as tasks frequency except tasks discretion indicator which is interpret as the intensity of tasks performed during work. For comparability reasons tasks indices have been standardised to have within-country mean equal to two and within-country standard deviation of one with proper post-sampling weighting.

In sum, the task indices I exploit for Eq. (5) of my methodology are: ICT (good proxy of cognitive/analytical tasks frequency connected with activities which demand computer literacy), influence (good proxy of interpersonal tasks), physical and tasks discretion for all tasks performed within individual's occupation. OECD (2016) classifies the selected tasks indices entailing the following aspects:

- *ICT*: Use computer; e-mail; Internet for information; Internet to conduct monetary transactions; spreadsheets; word processing; write or prepare computer code; real-time discussions using Internet; overall level of computer use in terms of complexity.
- *Influence*: Selling products or services; making speeches or presentations; advising; persuading or influencing others; negotiating; instructing, training or teaching others.

[33] For more information about job/everyday specific tasks and their clusters see OECD (2016, pp. 41-42, Box 2.1).

- *Physical*: Working physically for long periods; use of fine motor skills; working physically for a long period.

- *Tasks Discretion*: Choosing or changing sequence of job tasks, the speed of work, working hours; choosing how to do the job.

Albeit, there is no need to standardise the tasks indices for the analytical purposes of my analysis, I cannot provide any summary statistics for the reader or compare tasks frequency/intensity across countries because of the pre-standardisation by PIAAC experts. Unlike skills domains, tasks indices are not strongly correlated with the highest correlation of 0.23 between ICT and task discretion, whilst the correlation of ICT with the influence and physical tasks equals to 0.22 and -0.11, respectively. In addition, the value of corresponding correlation of numeracy scores with the selected tasks indices does not surpass the value of 0.30 in absolute terms. I use the selected tasks indices for my empirical analysis in Section 6. I usually refer to these tasks with the names of OECD (2016), as I mentioned above. Namely, I mention ICT tasks as either cognitive or analytical tasks because they constitute a good proxy according the definition of OECD (2016). In the same spirit, I refer to influencing tasks as interpersonal and physical as manuals tasks. Discretion in-the-job tasks is also mentioned as tasks intensity during the description of my empirical estimates.

4.4 Descriptive Statistics

The observations for each set of variables varies markedly due to numerous missing values and measurement errors. Only the scores of the three skill domains assessed (i.e. numeracy, literacy and problem-solving in technology-rich environments) do not face substantial issues. However, I focus only on numeracy scores because is one of the main parameters of my interest and the most comparable skill measurement across countries (see discussion in Sub-section 4.2). The total amount of observations in the pooled international sample is 133,017[34]. Full PIAAC sample includes workers of every job pattern (i.e. full/part-time and public/private sector), the self-employed individuals and the unemployed. The major reduction of my sample comes from the missing values around the gross hourly wage (in PPP U.S. dollars) which is the dependent variable in my empirical analysis and restricting the values to workers aged 16-65 excluding the self-employed[35] and non-employed. This decrease my sample to 76,026 observations. Furthermore, I clear the missing observations of the variables related to gross hourly wages (keep positive non-zero values), gender, work experience, age,

[34]With the Russian Federation the total number of observations is 136,909. But I exclude her from my analysis due to mistakes during the data collection procedure and because her sample does not contain the population of the Moscow municipal area. Thus, the data of the Russian Federation are not representative of her entire population aged 16-65 as OECD (2016, p. 61) underlines.

[35]I drop these observations from my sample because the data related to their earnings are prone to measurement errors according to Pokropek and Jakubowski (2013) and Hanushek et al. (2013).

years of schooling (defined as the highest school attainment) and numeracy test scores. My sample drops to 49,447. At last, I trim the the bottom and top one percent of hourly wage distribution diminishing the sample to 48,507. Figure A-1 depicts the hourly wage distribution of the entire international sample.

PIAAC demonstrates great heterogeneity in many aspects. Table A-1 presents the descriptive statistics for entire sample of workers aged 16-65 in the 22 selected countries. Sampling size of each country differs substantially. The United Kingdom has the largest sample with 4,040 observations, while Greece has the smallest sample with 768 observations. Beginning from assessed numeracy skills (see Figure A-2 for detailed ranking), the participants' average performance in Japan is the highest, in contrast to respondents in Chile who illustrate the lowest scores. Furthermore, Table-A1 shows interesting differences across counties with respect to average years of schooling, actual work experience and age. School attainment in Ireland and Lithuania surpasses 15 years, while in Slovenia hardly reaches 12 years. The Czech Republic and Denmark have the most experienced workers on average with 25 years of work experience and more, while the least experienced workers can be found in Chile and Poland with less than 16 years of work experience. Low years of work experience in Poland can be explained by the fact that the average age of her sample is around 34 years old, while the mean age of the pooled sample equals to 41 years old. Conversely, Denmark's participants are the oldest with an average age of 45 years old.

The heterogeneity across countries persists also on the job patterns such as the share of employees in public sector and proportion of people working full-time. Namely, public employment share ranges from 48 percent in Greece to 15 percent in Japan. The heterogeneity in the proportion of respondents working full-time across countries is more limited averaging to 80 percent, but the Netherlands constitute an interesting exception where 39 percent of participants was consisted of part-time employees. Moreover, females share of the pooled sample as well as in many countries is more or less balanced. In the samples of Chile, Cyprus, the Czech Republic, Estonia, Ireland and the United Kingdom the corresponding share surpasses 55 percent, whilst the highest females share is observed in Lithuania reaching 60 percent. Countries' samples vary also in terms of native residents. Namely, five countries (Japan, Poland, Korea, Chile and the Czech Republic) merely included any immigrant workers in their samples, in contrast to Denmark, Ireland and Israel where about 20 percent of their labour force in consisted of immigrants.

It is worth mentioning the marked cross-country variation in gross hourly earnings and the corresponding inequality measured as the ratio of the highest and lowest 10th percentile of hourly income distribution. Labour market in Norway and Denmark rewards its workers, on average, with 25 U.S. dollars per hour, whereas employees in former Soviet Democracies (i.e. Czech Republic, Estonia, Lithuania, Poland, Slovak Republic and Slovenia) earn a bit more than 11 U.S. dollars. Wage inequality is largest in Korea and Chile, where a worker at the upper 10th percentile of the wage distribution levies more than four times as much as an employee in the bottom 10th percentile. Figures A-3 and A-4 give a clear view about the the ranking of average hourly wages and income inequality across countries, respectively.

5 Returns to Skills Across Different Countries

One of the first questions I seek to address in my study is in what extent different skill levels affect labour market earnings, others things equal? PIAAC data does not only provide the opportunity to examine how the returns to numeracy skills vary across countries, but also how they behave by specific sub-groups. I derive a few estimates for specific sub-groups in order to grasp how they contribute to the average return to skill of the sampled population. In this section, I estimate my wage regression Eq. (3), which formulates log of hourly wage as function of skills, gender and a quadratic polynomial of potential experience (age minus years of schooling minus six), for the whole sample of employed individuals[36].

5.1 Comparison of Returns to Schooling and Numeracy

Initially, following the empirical conceptual framework of a major part of the literature, I am interested to compare the estimates that the standard Mincerian and direct skill measurement methodologies produce (see discussion in Section 2). Thus, I begin my analysis by estimating my wage regression substituting C of Eq. (3) with school attainment and standardised numeracy scores, afterwards. Table A-2 illustrates the estimates of Mincer's standard wage regressions and Table A-3 presents the baseline estimated returns to numeracy within a Mincerian analogue formulation. Since I standardise[37] numeracy scores, the estimated coefficient should be interpreted as the the percentage change of gross hourly earnings related to a one-standard-deviation of numeracy skills. Indeed, Figure A-5 demonstrates the substantial difference between the returns to schooling and numeracy. Table A-4 shows in detail the differences in estimated returns to schooling and numeracy across countries. All countries show larger returns to numeracy than schooling except Greece. These results are in line with the econometric literature that highlights the downward bias that schooling variable has (see Card (2001)). However, Greece is a peculiar case because the continuous recession over the last eight years may have diminished the returns to numeracy skills considerably. Therefore, due to economic strains the labour market is not able to reward sufficiently the workers, even if they increase their numeracy skills substantially.

The highest returns to numeracy can be observed in the United Kingdom, Ireland, Israel and Spain surpassing 15 percent. On the other hand, an increase of a one-standard-deviation in numeracy skills raises the gross hourly wage no more than eight percentage points in Greece and participating Former Soviet

[36] I include all types of employed aged 16-65 at the time of the PIAAC interview (i.e. full/part-time; public/private sector).

[37] A within-country mean of zero and within-country standard deviation of one.

Republics (the Czech Republic, Estonia, Lithuania, Poland and Slovak Republic) except Slovenia. Belgium, Japan and the Netherlands demonstrate average returns to numeracy around 14 percent. In Cyprus as well as in Finland, Denmark, Norway and Slovenia an increase of a one-standard-deviation in numeracy skills induces an increase in hourly wages averaging 10 percent, in contrast to Italy, Korea and Chile which hardly reach 10 percent. Table A-3 shows the estimates of workers' hourly wage formulated as a concave function of potential experience (age minus years of schooling minus six) accompanied with a binomial gender indicator, which checks for wage gap in the whole sample of respondents aged 16-65. Indeed, there is consistent difference in hourly earnings between the two genders across countries. In Chile, Greece, Ireland, Israel, Italy, Poland and Slovenia there are statistically insignificant gender differences in earnings, whereas male workers in six counties (Cyprus, Estonia, Finland, Japan, Korea and Norway) earn higher wages by 10 percentage points or larger on average than their female counterparts.

Interestingly, as Table A-5 depicts, the returns to numeracy remain robust after adding additional controls for 10 one-digit occupations (ISCO) categories and 22 one-digit industry (ISIC) categories, as defined by International Labour Organization (ILO). Column (5) controls for one-digit industry categories and shows that within industries the average return to numeracy is 10.5 percent. Adding occupation fixed effects in column (6), the estimated return to numeracy are lower than controlling for industries. Within occupations an increase of a one-standard-deviation in numeracy skills raises by 6.5 percentage points the hourly wage on average. The reduction of overall estimated coefficients indicates self-selection of workers into higher-paying occupations and industries. In addition, I can conclude also that selection into occupations and industries explains partly the variation in returns to numeracy. Finally, columns (1) and (2) show why I should include country fixed effects in the pooled estimations. Country fixed effects improve substantially the explanatory power of my empirical model because they control for those characteristics that remain relatively unchanged across the 22 different countries.

5.2 Age Varying Heterogeneity of Returns

As discussed in Section 2, the majority of the relevant studies relate their estimates on early-career workers of the United States due to the existence of rich datasets. However, these estimations do not necessarily mean that describe sufficiently the returns to skills in other economic establishments and labour markets. In addition, Mincerian empirical model presumes that the cross-sectional labour market earnings of a 50-year-old tertiary graduate is a sufficient approximation of what a 25-year-old tertiary graduate should expect in the following years. The specific assumption using cross-sectional data is not entirely correct and the current earnings are not always in line with the expectations about the lifetime earnings (see discussion in Björklund (1993) and Haider and Solon (2006)). In my sample, the age of participants varies from 16 to 65 years old. In this sub-section, I investigate how returns to numeracy vary across different age groups. This is handy because helps me not only to gauge how different age sub-groups contribute to the overall return to numeracy for each country, but also on aggregate for the pooled sample. To test the hypothesis that the returns are different across age groups, I organise my data in four groups with respect to respondent's age. Namely, these age groups are: i) youth employees (16-24); ii) entry-age (25-34); iii) prime-age (35-54); and iv) exit-age (55-65) workers who are near to retirement.

Figure A-6 demonstrates the returns to numeracy in each defined age group for the pooled sample. It is apparent that the returns to skill are higher for workers aged 35-54 and the overall average returns are driven by the prime-age sub-group because is substantially larger than the others (see the average age in Table A-1). This outcome is quite reasonable because workers at this age usually reach the climax of their working career and a potential improvement of their numeracy skills may lead them to highly paid positions or trigger a promotion easier, whilst the reduction of returns among exit-age workers potentially happens because productivity usually drops and space for either skill improvement or promotion to higher job positions is limited near retirement. Haider and Solon (2006) provide a similar explanation and they highlight that the returns to skills of prime-age workers constitute the best proxy for the lifetime returns. Additionally, Altonji and Pierret (2001) argue that the specific phenomenon occurs because employers need time to observe the skill levels of their employees and match wages properly.

5.3 Returns in Different Job Sub-groups

Wage determination literature contains numerous discussions that the type or sector of employment may affect earnings' profile and consequently their returns to skills. In other words, individuals working in private sector might face different challenges than their counterparts working in public sector. In the same spirit, I can infer that those who are working either full- or part-time. Therefore, different types of employment may be characterized by different returns to skills. In order to explore this plausible heterogeneity in returns to numeracy, I estimate my simple wage equation Eq. (3) for each job profile separately for the whole sample including all ages (16-65). The estimates reveal that considerable heterogeneity does exist for different types of employment. Figure A-7 depicts the outcomes for the pooled sample, while Table A-7 presents the detailed estimations for each country.

At fist, the average estimated returns to numeracy in private sector (13 percent) are higher than in public sector (10.7 percent) for the whole international sample. Accordingly, the returns for those working full-time[38] and part-time demonstrate the same behaviour (13.1 and 10.2 percent, respectively). The estimates for the whole sample are statistically significant at one percent level for each defined job sub-group.

[38]In PIAAC survey, full-time workers are defined as those working at least 30 hours per week.

Table A-7 shows that the returns in private and public sector follow the same patter with different magnitudes across countries with a few exceptions. Namely, the aforementioned returns are almost identical in Belgium, France, Italy, the Netherlands, while in Finland and Cyprus workers in public sector experience higher returns than the workers in private sector. Finally, in all counties the estimated returns of full-time workers surpass the corresponding returns of their part-time counterparts. In particular, numeracy returns of part-time workers in Chile, Estonia, Greece, Italy, Lithuania, Poland and Slovak Republic are statistically insignificant.

The results seem quite logical. Full-time professions usually require more advanced skills than the part-time jobs and for that reason labour market provides higher rewards and ultimately returns to their numeracy skills. The difference in the returns to numeracy between public and private sector workers is a bit obscure and a reasonable interpretation should be given. On the one hand, public servants should have a standard level of skill to be hired and service their fellow citizens. On the other hand, private sector does not require a standard amount of skills but the advanced skills could be rewarded with higher wages and promotions. However, the same cannot be happened in the public sector because the opportunities for highly paid positions and are limited even if public servants augment their cognitive skills to a greater level. Pissarides (2000) provides a similar argument and his analysis concludes that the private sector reflects better labour market rewards with respect individual's skill levels and productivity.

5.4 Heterogeneity of Returns in Different Societal Sub-groups

In wage determination debate, many researchers have already highlighted that different societal sub-groups face different challenges and requirements from labour markets such as females or immigrants[39]. Thus, this potential source of heterogeneity in wage determination should be addressed. Figure A-8 illustrates the estimated coefficients for the pooled international sample and Table A-8 provides details for each country individually. In the entire sample there are slight differences in the estimated returns to skills, but the pooled patterns are not uniform in all participating countries. Firstly, men on average enjoy higher returns to skills (13.2 percent) than women (11.9 percent) but the difference is relatively modest. However, in Belgium and Ireland females have higher returns than males, while in Spain the returns to numeracy for both genders are almost identical. The higher returns for male workers may be interpreted as a sign of discrimination in the labour market and men with higher numeracy skills tend to levy higher wages than women with the exact same skills. However, the differences in these returns should be interpreted prudently because women follow different earnings trajectories than men due to interruption of their working careers because of maternity (Oaxaca (1973)) and other institutional or cultural factors (Psacharopoulos and Tzannatos (1992)). Secondly,

[39]In PIAAC survey, immigrant workers are defined as those workers born abroad with at least one parent also born abroad.

immigrants in the pooled sample tend to have slightly higher returns to numeracy (12.9 percent) than the native employees (12.5 percent). The slightly higher returns for immigrants may signal that labour market is unbiased, but can be interpreted on the other way around. One case could be that immigrants earn on average less than the natives and an improvement of their skills has a larger marginal impact on their earnings. Belgium, Chile, Cyprus, Ireland, Korea, the Netherlands and the United Kingdom follow this pattern. Conversely, in seven countries (Estonia, Finland, Greece, Italy, Japan, the Slovak Republic and Spain) labour market tend to discriminate against immigrants by rewarding them with lower returns to skills than native employees.

6 Putting Tasks to the Test

After reviewing the heterogeneity of returns to numeracy across different sub-groups and they contribute to the aggregate estimations of the pooled sample, I augment my empirical model by including a few job-related tasks, as depicted in Eq. (5), which I call "task-based" approach or model. Tasks keep gaining ground as explanatory variables in both theoretical and empirical analysis. The sophistication behind conceptualization of tasks can be summarised by the accented phrase of Autor and Handel (2013) that "**. . . the tasks that a worker performs on the job are an application of that worker's skill endowment to a given set of activities and workers can modify these task inputs as job requirements change**". Therefore, at least from an empirical perspective, the variation in job tasks may be a good predictor of wage differentials.

Table A-9 shows the added value by the tasks and the robustness of their estimated returns for additional controls associated with 10 one-digit occupations (ISCO) and 22 one-digit industry (ISIC) categories for the entire international sample of workers aged 16-65. Columns (1) to (4) add one by one my selected tasks indices to investigate how they affect the estimated return to numeracy. The aggregate magnitude of return to numeracy skills keeps decreasing when an additional task index is added. Column (4) inserts all the tasks with country fixed effects and the average estimated return to numeracy reduces from 13 to 8.8 percent after an increase of numeracy skills by a one-standard-deviation from their mean. The specific column also illustrates that the returns to ICT (good proxy of cognitive/analytical tasks) and influence tasks surpass five percent, while a one-standard-deviation increase in tasks discretion raises worker's hourly gross wage by around three percentage points on average. Conversely, a one-standard-deviation increase in physical tasks frequency diminishes worker's earnings by approximately four percentage points. Column (6) demonstrates that controls for occupation and industry categories diminish both returns to numeracy and tasks but still retain their statistical significance at one percent level. In particular, average returns to numeracy are reduced by 37 percentage points, while the reduction of returns to tasks varies from five for the tasks discretion to 43 percentage points for the interpersonal tasks, respectively. The reduction in the aggregate return to skills underlines the selection of workers into higher paying occupations and industries. Additionally, the similar reduction of returns to tasks indicates the self-section of workers into those occupations and industries which compensate the selected tasks better. In other words, there is not random assignment of workers into job tasks (Autor and Handel (2013); Yamaguchi (2016)).

Furthermore, I estimate Eq. (5) for each country participated in PIAAC survey to examine if the returns to tasks vary across countries. This is quite helpful because the frequency or discretion of tasks may be identical across counties, but labour markets might reward tasks differently according to economic structure of each country. Table A-10 presents analytically the derived estimations including all the tasks indices for the pooled sample and separately by country. Table A-3 shows the identical estimates without adding tasks indices (i.e. baseline estimates). At first, my results suggest that the estimated returns to numeracy decrease throughout countries with different magnitudes, while the significance level of few estimated returns for specific countries drops. To precise, the returns to numeracy in Greece and Lithuania are statistically significant at five and 10 percent level, respectively. The estimated returns to numeracy for the remaining 19 countries preserve their statistical significance at one percent level. Secondly, Figure A-9 demonstrates that 10 countries (United Kingdom, Ireland, Japan, Poland, Belgium, the Netherlands, Finland, Denmark, Italy and Lithuania) face a prominent reduction, while the returns in other countries such as Cyprus, Chile, Korea and the Slovak Republic merely change. Still, even with all tasks indices included, estimated returns to numeracy in the countries with the highest returns (Israel, the United Kingdom, Cyprus, Ireland, Spain and France) are approximately twice as large as the countries with the lowest ones (Poland, Estonia, Greece, Lithuania and the Czech and Slovak Republics). The estimated returns in the remaining 10 countries in between vary from six to 10 percent.

The variation in returns to tasks is quite prominent across countries. At first, as Table A-10 illustrates, cognitive (ICT) tasks are best rewarded in Japan and the United Kingdom where a one standard-deviation increase in their frequency augments gross hourly wage by 9.2 percentage points, while in four countries (Cyprus, Greece, Italy and Poland) does not have any statistical significant impact on workers' earnings. Secondly, interpersonal (*influence*) tasks are statistically significant in all economies and their returns vary from two (Norway) to 13.5 (Cyprus) percent. Thirdly, returns to manual (*physical*) tasks frequency contribute negatively to workers' income throughout countries with few exceptions (Denmark, Estonia, Korea and Lithuania) where physical tasks frequency do not have any statistically significant impact on wages. This result is also in line with Autor et al. (2003), who argue that due to computerization physical tasks become easily codified and are usually performed by less skilled/educated workers with lower wages. Finally, the highest returns to tasks discretion of around six percent are observed in Estonia and Italy, whilst five labour markets (Chile, Cyprus, Greece, Japan and Korea) do not provide any additional compensation for changes in the intensity of tasks performed on the job. For the remaining countries, the coefficient estimates on job tasks intensity varies from one to four percent.

6.1 Robustness Check of Tasks Indices and Returns to Skills

In order to check the robustness of my estimated returns of both returns to numeracy and tasks, I follow the sophistication of Haider and Solon (2006) who find that the estimated returns to skills for full-time prime aged (35-54) workers approximate preciser the lifetime returns. In this way, not only I test the robustness of my estimated returns, but also I derive indicative estimations which might approach returns to job tasks and numeracy skills in the long-run, using a more homogeneous sub-sample. Hanushek et al. (2013, 2017) mention that prime-age workers constitute a credible sub-sample because it isolates the direct labour market effects due to the fact that the influences from family, health condition, changes in tastes and preferences are limited. But, the most crucial is that the specific part of the labour force has a strong commitment to their job if we consider that workers reach the climax of their professional career. Table A-11 presents the analytical estimates for the restricted sample, as described above.

Figure A-10 illustrates that the returns to numeracy skills increase for each country with different magnitudes, while the sorting of counties remains relatively unchanged. Chile along with Greece and Lithuania constitute interesting exceptions and their estimated returns to skill become statistically insignificant. Remarkably, the patterns of returns to tasks remain more or less identical and a little bit increased except returns to tasks discretion which become statistically insignificant for 14 out of 22 countries. Furthermore, Figure A-11 unveils how the aggregate returns to tasks change between the entire sample of employees aged 16-65 and the sub-sample which consists only of prime aged (35-54) workers. Although, in both cases the estimated returns retain their statistical significance at one percent level, there is a significant limitation of my empirical analysis which jeopardise the validity of causal link between tasks frequency/intensity and labour market earnings. As Autor and Handel (2013) document, there is a definite self-selection into tasks and an empirical Mincerian framework or a Mincerian analogue is not able to offer a deeper insight into the nature of the specific self-selection. My estimations controlling for industry and occupation fixed effects in column (6) of Table A-9 certify that workers tend to select those professions which reward with higher wages the selected tasks and their discretion. Therefore, an alternative empirical or even a theoretical approach[40] is needed to establish a causal interpretation. Autor and Handel (2013) summarise this limitation in a very clear phrase: **"...should we expect the coefficients on job tasks in a wage regression to capture the equilibrium, economy-wide price of the tasks? The answer is no."**.

[40] See task-based Roy modelling in Autor and Handel (2013) and Yamaguchi (2016).

7 Cross-Country Differences in Returns to Skills

Until now my study indicates that returns to skills vary substantially across countries. This heterogeneity of returns to numeracy remains when I augmented my empirical model by conceptualizing in-the-job tasks. This means that the returns to skills may vary systematically across countries due to different institutional features such as labour market protection, size of labour unions, productivity levels and economic growth. Therefore, in this section, I orient my analysis to establish stylised facts associated with unique county characteristics which may affect systematically the returns to numeracy across countries. For this part, I drop the job tasks due to the concerns of self-selection, but I keep restricting my entire international sample to full-time workers aged 35-54 in order to approach the lifetime returns accounting for economies' features with a more homogeneous sub-sample.

In the past years, especially after the bust of the global financial crisis in 2008, governments introduced many labour market reforms in order to stabilise economies and sustain the well-being of their citizens. This fact motivated my analysis to examine whether these institutional reforms interact with the rewards of numeracy skills. To answer this question, I have to adjust my empirical analysis. In particular, I augment the simplest version of my wage equation, as depicted in Eq. (4), by adding interactions terms between the standardised individual (i) numeracy scores (C) and a variety of measures of country-specific characteristics (Λ_c), while I preserve country fixed effects (η_c), for $c = 1, \ldots, 22$ countries[41]. Thus, the final algebraic form is the following:

$$\log y_{ic} = \eta_c + \alpha_0 + \alpha_1 C_{ic} + \beta_1 (C_{ic} \times \Lambda_c) + \alpha_2 PE_{ic} + \alpha_3 PE_{ic}^2 + \alpha_4 G_{ic} + \epsilon_{ic} \tag{6}$$

I do not include country-specific measures (Λ_c) as an individual parameter in Eq. (6) because country fixed effects absorb the major effects from these county-level measures due to the fact these measures remain unchanged for individuals within countries and differentiate only across countries. Except α_1 the parameter of interest is β_1 coefficient which can be interpreted as how different country-level characteristics affect the estimated returns to numeracy skills. In this empirical formulation, β_1 actually varies only across countries and for that reason the standard errors should be clustered with respect to the country level. Another detail that should be mentioned is that any bias in the estimated returns to skills would not distort my estimates because bias is associated with the the relative returns across countries. Finally, to simplify the interpretation of the interaction term, I de-mean all country-level measures incorporated in Λ_c.

To perform the described analysis, I extract data about the structural features of PIAAC participating economies mainly from OECD and the World Bank. Employment protection legislation (EPL)[42] index

[41]See Hanushek et al. (2013, 2017) for additional information about the specific methodology.

[42]The employment protection indicator is the weighted sum of sub-indicators concerning the regulations for individual dis-

measures how stringent is the protection against individual and collective dismissals for those workers with regular contracts. The higher the EPL index is, the higher the level of employment protection is in a country's labour market. Union density represents the share of workers who are member of labour unions. Public employment share[43] indicates the share of workers in public sector. Moreover, I use data for gross domestic expenditure on research and experimental development (GEDR, henceforth), GDP per capita growth, change in labour productivity and a binary minimum wage indicator which takes the price one if an economy has a statutory minimum wage and zero otherwise.

Table A-13 presents the estimated results for countries' selected institutional factors. At first, I assess each country-level characteristic separately. Employment protection, public employment share and GEDR interactions with returns to numeracy skills remain statistically significant. That is, economies with larger public sector size, stricter labour protection have systematically lower returns to skills, while higher investments on research and development (as percentage of GDP) lead systematically to higher returns to numeracy. For instance, the estimated interaction in column (1) suggests that a 100 percentage-points increase in employment protection diminishes by 4.5[44] percentage points the wage increase for each one-standard-deviation increase in numeracy skills. By contrast, a 100 percentage-points increase in GEDR raises by 1.6 percentage points the wage increase for each one-standard-deviation increase in numeracy skills. The results are reasonable if we think that additional employment protection (or less flexible labour market) and collective bargaining increase the statutory wages and there is less space for raises if employees improve their skills (Frandsen (2012)). Similarly, wages in public sector are usually higher than the relevant wages in private sector but the promotion opportunities to highly paid positions are capped. This can be translated into lower overall returns to skill, whilst larger public sector may skew the function of the labour market (Pissarides (2000)). At last, higher GEDR may raise estimated returns because they complement cognitive skills due to the fact that the specific investments create facilities and job vacancies required for contemporary technology-based economies to function (Ingram and Neumann (2006)).

I test further the robustness of the estimated interactions by including both sets of occupation and industry fixed effects. This helps me to check whether the outcomes are associated with differences in countries' occupation or industry characteristics. Surprisingly, as column (9) depicts, the interactions of employment protection and public employment results remain statistically significant, whereas the GEDR's interaction lose their significance. This means that the selection into occupation or industries explains partly the returns to numeracy and the variation originates within the empirical model rather than occupation or industry specifications. GEDR loses its statistical significance because occupations and industries which use

missals (weight of 5/7) and additional provisions for collective dismissals (2/7), incorporating 13 data items (see Venn (2009) for further details). Information and the additional data I use, can be found in Table A-12 to the Appendix A: Tables.

[43] Public employment share is calculated from PIAAC data.

[44] The corresponding reduction is approximately 3.8 percentage points for public employment share.

more technology might be associated with higher cognitive skills but not with additional earnings. Hence, I conclude that countries with stricter labour protection legislation and higher public employment share are characterised by systematically lower returns to numeracy.

8 Summary and Conclusions

Human capital constitutes a key aspect for both micro- and macro-economic literature. In particular, in micro-economic literature human capital is regarded as the main factors which explain the systematic wage differential between individuals. However, the extant empirical studies mainly base their estimates on the Mincerian establishment leading them to substantial bias. The reason behind this bias is that the Mincerian wage equation presumes that schooling is the unique systematic source of skills differences, ignoring other interesting factors which may systematically influence skills. Except the instrumental variable technique to overcome this problem, the direct skill measurements were introduced. Empirical framework evolved further by entering job tasks to examine the differences in workers' earnings. Although, these techniques give a picture how modern labour market rewards workers, the lion's share of empirical evidence focuses solely on samples consisted of young employees in the United States (Hanushek et al. (2013, 2017)). Thus, the estimated returns to skills and tasks may not be representative for older workers and other economic establishments or labour markets. In this study, I examine the returns to cognitive skills and selected tasks across 22 different countries. The new and extended PIAAC survey provides international comparable data which permits us to investigate how knowledge-based economies evaluate skills and task performed on the job.

My first observation is that higher school attainment and numeracy skills are systematically associated with higher wages in all 22 countries, but their returns differ substantially. In particular, the returns to schooling are lower than 10 percent which refers to the fact that they suffer from a downward bias. Only in Greece the returns to schooling surpass slightly the returns to numeracy, but this might be happening because of the continuous recession which restricts the capacity of Greek labour market to compensate properly higher cognitive skills. Among workers aged 16-65, a one-standard-deviation in numeracy skills from their mean leads to an average increase of gross hourly wage by 13 percentage points across countries. One intriguing finding is that marked heterogeneity in returns to numeracy exists across countries. Estimated returns to numeracy in the countries with the highest returns (the United Kingdom, Ireland, Israel, Spain and France) are approximately twice as large as the countries with the lowest ones (Poland, Estonia, Greece, Lithuania and the Czech and Slovak Republics). The estimated rates of returns for the remaining countries in between vary from 10 to 14 percent.

Moreover, different sub-groups such as full-time, private sector, female and immigrant workers unveil interesting patterns of returns to skill meaning that they face different challenges and requirements in the labour market. But the most interesting is the heterogeneity of returns across different age groups. Prime-age workers (35-54) demonstrate quite persistently higher returns to numeracy skills of about four percent than entry-age (25-34) and exit-age (55-65) workers, while the returns to skills for the youth employees reach merely four percent. This means also that the current returns do not approximate sufficiently the lifetime returns to skills. Intriguingly, only former Soviet Democracies (the Czech and Slovak Republics, Estonia and Lithuania) do not follow the specific age pattern, which might refer to the fact that during the transition phase to a market-economy scheme the older workers lost a considerable part of their human capital (Mertaugh and Hanushek (2005)).

After checking the association of labour market earnings with skills, I enrich my empirical model with tasks indices. The average return to numeracy across countries decreases from 13 to 8.8 percent. A one-standard-deviation increase in frequency of cognitive/analytical and interpersonal/influence tasks raises gross hourly wages by somewhat more than five percentage points, while an identical change in-the-job tasks intensity induces a three percentage-points increase in earnings approximately. On the other hand, physical tasks demonstrate negative returns up to four percent. Moreover, I check the robustness of my estimates in two ways. At first, for the whole international sample of workers aged 16-65, I add occupation-industry fixed effects. Secondly, following the sophistication of Björklund (1993) and Haider and Solon (2006), I restrict my estimations to full-time prime age (35-54) workers in order to approximate the lifetime returns for both tasks and numeracy skills with a more homogeneous sample. Remarkably, in both cases the estimated returns maintain their statistical significance and cross-country heterogeneity. Nonetheless, the causal relationship between tasks and labour market earnings is fragile because there is a clear self-selection into occupations that remunerate greater the specific job tasks (Autor and Handel (2013)).

Having analysed the dynamics of returns to skills and tasks across countries, in the last part of my analysis I examine whether the returns to skills vary across countries due to differences in economic structure and labour market institutions. Interestingly, countries with stricter employment protection and larger public employment share have systematically lower returns to numeracy skills, whilst level of unionism, GDP per capita growth, changes in real productivity, minimum wages do not systematically affect the returns to numeracy skills. But, these results establish only stylised facts about the factors which are systematically related to returns to skills across countries and they are not going deeper for specific countries.

My analysis contributes to the deeper understanding on how technology-based labour markets reward cognitive skills and job tasks. By underling how modern economies value skills, effective policies can be organised in order to augment citizens' well-being and mitigate inequality. Such public policies could be: i) excellent preschool through high school education; ii) broad access to post-secondary education; iii) good public health; and iv) high-quality home environments. These policies could lessen inequality in two ways. At first, enabling a larger fraction of adults to attain high productivity and well-paid jobs to make a living. Secondly, raising the total supply of skills available to the economy eases the skill premium (Autor (2014)). My results certify the argument by Caselli (2005) that economic prosperity connects with different county-level characteristics.

Nevertheless, my empirical findings should be interpreted prudently. On the one hand, higher numeracy skills are partly associated with extension of school attainment. On the other hand, there is self-selection of workers into occupations which pay higher specific tasks. It is apparent that there are signs of endogeneity which may distort the causal relation between higher skills (or tasks intensity/frequency) with higher workers' earnings. Still, a causal interpretation for the estimated coefficients should be established. In addition, another flaw exists in my analysis. Although, PIAAC survey provides international comparable cross-sectional data, it lacks panel aspect which means that we are not able to examine changes over time. Technological advance is a dynamic process and it would be useful to examine whether changes in technology systematically affect returns to skills and tasks. At last, the vast of majority of the literature focuses either on the link of labour market earnings with students' performance or workers' skill levels. Thus, in order to fully fathom the economic implications on earnings, the analysis of school achievements and direct skills measurements should be combined.

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Appendix A: Tables

Table A-1: Descriptive Statistics

Variables	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Gross Hourly Wage	17.89	19.86	16.14	17.15	11.22	24.96	12.90	19.15	15.92	12.90	22.97	14.90
	(10.35)	(8.46)	(11.21)	(10.80)	(6.34)	(9.54)	(7.45)	(7.67)	(7.88)	(7.54)	(12.19)	(9.69)
Wage Inequality	2.93	2.50	4.05	3.70	2.14	2.27	2.90	2.51	2.48	2.81	3.50	3.49
Numeracy	278.57	287.16	237.15	275.40	289.39	284.85	286.78	293.58	264.95	265.41	267.90	262.64
	(49.26)	(49.16)	(51.90)	(44.25)	(41.96)	(49.90)	(41.74)	(46.47)	(54.20)	(47.39)	(49.43)	(58.49)
Age	41.05	40.49	39.62	39.45	39.75	45.44	40.22	42.70	41.60	41.98	39.57	39.92
	(11.49)	(11.02)	(11.52)	(10.96)	(11.65)	(11.80)	(11.43)	(11.88)	(11.12)	(8.98)	(10.82)	(11.99)
Schooling	13.58	12.98	13.67	13.58	14.42	13.51	13.16	13.26	12.11	13.72	15.81	13.56
	(2.93)	(2.58)	(3.09)	(3.12)	(2.76)	(2.63)	(2.62)	(2.90)	(3.43)	(3.01)	(2.82)	(2.62)
Experience	19.05	19.13	15.57	17.14	28.25	24.87	18.82	19.97	19.79	17.41	18.04	19.22
	(11.67)	(11.36)	(11.23)	(11.03)	(11.83)	(12.48)	(11.47)	(12.07)	(11.76)	(8.95)	(10.58)	(11.65)
Female (share)	0.48	0.48	0.43	0.55	0.41	0.50	0.46	0.49	0.48	0.48	0.55	0.46
Public (share)	0.33	0.31	0.22	0.35	0.31	0.42	0.32	0.38	0.28	0.48	0.33	0.37
Full-time (share)	0.83	0.76	0.84	0.92	0.94	0.82	0.94	0.90	0.83	0.87	0.75	0.83
Natives (share)	0.91	0.93	0.98	0.88	0.97	0.82	0.91	0.96	0.90	0.92	0.79	0.77
Observations	48,507	2,570	943	1,986	1,507	3,977	2,132	2,887	3,429	786	2,525	1,746

Variables		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Gross Hourly Wage		16.21	16.21	18.83	11.72	21.31	25.39	11.88	11.10	11.62	14.92	18.35
		(9.68)	(10.80)	(13.60)	(6.84)	(9.88)	(9.36)	(6.67)	(5.87)	(4.70)	(8.49)	(10.60)
Wage Inequality		2.96	3.68	4.50	2.50	2.86	2.27	2.50	2.36	2.27	3.00	3.41
Numeracy		262.63	295.21	270.81	287.29	288.09	290.55	277.33	294.45	278.61	258.84	274.86
		(47.75)	(42.74)	(42.74)	(43.25)	(45.94)	(50.00)	(46.33)	(38.38)	(45.90)	(47.64)	(47.87)
Age		41.96	42.30	39.72	41.98	41.96	41.98	34.05	40.63	41.78	40.66	39.57
		(9.97)	(11.97)	(10.80)	(11.74)	(11.74)	(11.79)	(11.76)	(11.12)	(9.54)	(10.30)	(11.48)
Schooling		12.56	13.55	13.88	15.22	13.71	14.84	14.20	14.56	11.60	12.42	13.42
		(3.71)	(2.36)	(2.94)	(2.48)	(2.40)	(2.31)	(2.71)	(2.70)	(1.72)	(3.48)	(2.33)
Experience		18.20	19.34	13.54	19.74	20.79	20.27	12.51	19.01	19.39	17.75	19.38
		(10.31)	(11.73)	(9.95)	(11.69)	(11.38)	(11.65)	(11.50)	(11.45)	(10.81)	(10.82)	(11.34)
Female (share)		0.47	0.45	0.40	0.52	0.48	0.48	0.38	0.41	0.47	0.46	0.58
Public (share)		0.29	0.15	0.19	0.40	0.33	0.40	0.32	0.32	0.42	0.28	0.37
Full-time (share)		0.84	0.75	0.88	0.94	0.61	0.83	0.93	0.96	0.95	0.84	0.74
Natives (share)		0.91	1.00	0.99	0.96	0.92	0.87	1.00	0.98	0.93	0.89	0.89
Observations		1,785	2,788	2,350	1,129	2,629	3,130	1,616	1,171	1,302	2,079	4,040

Notes: Means, standard deviations (in parentheses) and numbers of observations for selected variables by country. Sample: employees aged 16-65. *Wage inequality*: gross hourly wage ratio between 90th and 10th percentile of wage distribution. *Gross Hourly Wage*: in PPP U.S. dollars. *Experience* refers to actual work experience. *Age*, *Schooling* and *Experience* denominated in years. *Source*: PIAAC.

Table A-2: Standard Mincerian Wage Regressions

Variables	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Schooling	0.065***	0.073***	0.054***	0.097***	0.045***	0.061***	0.033***	0.069***	0.065***	0.070***	0.087***	0.077***
	[0.0007]	[0.003]	[0.006]	[0.004]	[0.003]	[0.002]	[0.004]	[0.002]	[0.002]	[0.006]	[0.003]	[0.005]
Experience	0.020***	0.024***	0.002	0.030***	0.001***	0.025***	0.012***	0.022***	0.019***	0.009	0.033***	0.022***
	[0.0005]	[0.002]	[0.006]	[0.003]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.006]	[0.002]	[0.003]
Experience^2	-0.030***	-0.026***	0.002	0.023***	-0.02***	-0.035***	-0.030***	-0.028***	0.015***	0.011	-0.04***	-0.03***
	[0.001]	[0.005]	[0.012]	[0.005]	[0.006]	[0.003]	[0.006]	[0.004]	[0.003]	[0.012]	[0.005]	[0.007]
Female	-0.15***	-0.10***	-0.022	-0.17***	-0.11***	-0.12***	-0.24***	-0.22***	-0.14***	-0.061**	-0.07***	-0.12***
	[0.004]	[0.012]	[0.04]	[0.02]	[0.02]	[0.01]	[0.02]	[0.011]	[0.011]	[0.03]	[0.02]	[0.02]
R^2	0.42	0.32	0.08	0.29	0.15	0.30	0.10	0.39	0.30	0.20	0.28	0.22
Observations	48,507	2,570	943	1,986	1,507	3,977	2,132	2,887	3,429	786	2,525	1,746

Variables		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Schooling		0.060***	0.069***	0.071***	0.041***	0.083***	0.059***	0.035***	0.037***	0.088***	0.073***	0.096***
		[0.003]	[0.004]	[0.005]	[0.005]	[0.003]	[0.002]	[0.005]	[0.004]	[0.005]	[0.003]	[0.003]
Experience		0.029***	0.036***	0.012***	0.002	0.033***	0.024***	0.016***	0.0005	0.015***	0.019***	0.04***
		[0.003]	[0.002]	[0.004]	[0.004]	[0.002]	[0.002]	[0.003]	[0.003]	[0.004]	[0.003]	[0.002]
Experience^2		-0.034***	-0.057	-0.002	-0.005	-0.046***	-0.039***	-0.03***	0.008	-0.017*	-0.019***	-0.064***
		[0.006]	[0.005]	[0.009]	[0.009]	[0.005]	[0.003]	[0.007]	[0.008]	[0.009]	[0.006]	[0.004]
Female		-0.10***	-0.38***	-0.17***	-0.12***	-0.11***	-0.16***	-0.044**	-0.12***	-0.084***	-0.15***	-0.17***
		[0.02]	[0.02]	[0.02]	[0.03]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
R^2		0.23	0.31	0.13	0.07	0.35	0.31	0.08	0.08	0.21	0.30	0.31
Observations		1,785	2,788	2,350	1,129	2,629	3,130	1,616	1,171	1,302	2,079	4,040

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. *Female* is a binary gender indicator (1 for females; 0 for males) and *Experience* refers to the potential experience (age minus years of schooling minus six). *Experience*^{2} divided by 100. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported.

Source: Author's calculation & PIAAC.

Table A-3: Returns to Numeracy within Mincerian Framework; Baseline Estimates

Variables	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Numeracy	0.13***	0.14***	0.097***	0.13***	0.059***	0.12***	0.067***	0.13***	0.15***	0.066***	0.18***	0.16***
	[0.002]	[0.007]	[0.02]	[0.01]	[0.01]	[0.005]	[0.009]	[0.006]	[0.006]	[0.02]	[0.009]	[0.01]
Experience	0.024***	0.026***	0.002	0.026***	0.009***	0.028***	0.011***	0.031***	0.021***	0.015**	0.035***	0.028***
	[0.0006]	[0.002]	[0.005]	[0.003]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.006]	[0.002]	[0.004]
Experience^2	-0.040***	-0.037***	-0.005	-0.044***	-0.021***	-0.044***	-0.028***	-0.051***	-0.028***	-0.020	-0.064***	-0.040***
	[0.001]	[0.005]	[0.01]	[0.005]	[0.006]	[0.004]	[0.006]	[0.004]	[0.005]	[0.01]	[0.006]	[0.008]
Female	-0.095***	-0.035***	0.031	-0.11***	-0.068***	-0.071***	-0.19***	-0.13***	0.082***	-0.036	-0.006	-0.027
	[0.004]	[0.01]	[0.04]	[0.02]	[0.02]	[0.01]	[0.02]	[0.01]	[0.01]	[0.03]	[0.02]	[0.02]
R^2	0.37	0.24	0.03	0.12	0.05	0.21	0.09	0.25	0.21	0.04	0.21	0.17
Observations	48,507	2,570	943	1,986	1,507	3,977	2,132	2,887	3,429	786	2,525	1,746
Variables		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Numeracy		0.10***	0.14***	0.10***	0.061***	0.14***	0.12***	0.071***	0.047***	0.11***	0.16***	0.19***
		[0.01]	[0.009]	[0.01]	[0.01]	[0.007]	[0.005]	[0.01]	[0.01]	[0.008]	[0.01]	[0.006]
Experience		0.025***	0.033***	0.017***	0.0023	0.035***	0.026***	0.018***	-0.002	0.014***	0.018***	0.035***
		[0.003]	[0.002]	[0.004]	[0.01]	[0.002]	[0.002]	[0.003]	[0.003]	[0.004]	[0.003]	[0.002]
Experience^2		-0.040***	-0.053***	-0.027***	-0.0065	-0.055***	-0.045***	-0.036***	0.002	-0.016*	-0.027***	-0.064***
		[0.007]	[0.005]	[0.008]	[0.009]	[0.005]	[0.004]	[0.007]	[0.007]	[0.009]	[0.006]	[0.005]
Female		-0.013	-0.36***	-0.175***	-0.056**	-0.059***	-0.12***	0.025	-0.081***	-0.001	-0.058***	-0.096***
		[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]
R^2		0.09	0.28	0.07	0.03	0.25	0.26	0.06	0.03	0.13	0.15	0.26
Observations		1,785	2,788	2,350	1,129	2,629	3,130	1,616	1,171	1,302	2,079	4,040

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. *Female* is a binary gender indicator (1 for females; 0 for males) and *Experience* refers to the potential experience (age minus years of schooling minus six). *Experience*^{2} divided by 100. Pooled specification includes country fixed effects and gives same weight to each country. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported.

Source: Author's calculation & PIAAC.

Table A-4: Differences in Returns to Schooling and Numeracy

Country	Returns to Schooling	Returns to Numeracy	Difference of coefficients	Percentage change
Belgium	0.073	0.14	0.067	92%
Chile	0.054	0.097	0.043	80%
Cyprus	0.097	0.13	0.033	34%
Czech Republic	0.045	0.059	0.014	31%
Denmark	0.061	0.12	0.059	97%
Estonia	0.033	0.067	0.034	103%
Finland	0.069	0.13	0.061	88%
France	0.065	0.15	0.085	132%
Greece	0.07	0.066	-0.004	-6%
Ireland	0.087	0.18	0.093	107%
Israel	0.077	0.16	0.083	108%
Italy	0.06	0.1	0.04	67%
Japan	0.069	0.14	0.071	103%
Korea	0.071	0.1	0.029	41%
Lithuania	0.041	0.061	0.02	49%
Netherlands	0.083	0.14	0.057	69%
Norway	0.059	0.12	0.061	103%
Poland	0.35	0.071	0.036	103%
Slovak Republic	0.037	0.047	0.01	27%
Slovenia	0.088	0.11	0.022	25%
Spain	0.073	0.16	0.087	119%
United Kingdom	0.096	0.19	0.094	98%
Pooled	0.065	0.13	0.065	100%

Notes: Analytical comparison of numeracy skills (standardised to within-country mean of 0 and standard deviation of 1) and schooling (defined as the highest school attainment) in the first two columns. Third column shows the differences in levels of the estimated returns. Fourth column presents the percentage difference of the corresponding estimated returns. All the estimated rates of returns are statistically significant at 1 percent level. Pooled specification includes country fixed effects and gives same weight to each country. The specific table summarises the estimated returns in Tables A-2 and A-3. *Source*: Author's calculations & PIAAC.

Table A-5: Robustness of the Baseline Empirical Model

Variables	(1)	(2)	(3)	(4)	(5)
Numeracy	0.133***	0.128***	0.105***	0.065***	0.059***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Experience	0.023***	0.024***	0.022***	0.020***	0.019***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.0005]
$Experience^2$	-0.034***	-0.039***	-0.036***	-0.030***	-0.029***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Female	-0.073***	-0.095***	-0.119***	-0.124***	-0.117***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Country fixed effects		X	X	X	X
Industry fixed effects (22)			X		X
Occupation fixed effects (10)				X	X
R^2	0.11	0.37	0.40	0.46	0.47
Observations	48,507	48,507	47,999	47,918	47,552

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions pooling all countries with country fixed effects, weighted by sampling weights (giving same weight to each country). Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. *Female* is a binary gender indicator and *Experience* refers to the potential experience (age minus years of schooling minus six). $Experience^2$ is divided by 100. Number in parentheses reports the number of occupation and industry fixed effects. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported. *Source*: Author's calculations & PIAAC.

Table A-6: Heterogeneity of Returns to Numeracy by Age Group

Numeracy returns	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Age: 16-24	0.042***	0.065***	-0.044	-0.006	0.037	0.058**	0.028	0.025	0.027	-0.031	0.034	0.012***
	[0.006]	[0.016]	[0.073]	[0.039]	[0.035]	[0.024]	[0.026]	[0.026]	[0.021]	[0.142]	[0.042]	[0.041]
Age: 25-34	0.093***	0.094***	0.114***	0.113***	0.058***	0.080***	0.073***	0.088***	0.112***	-0.019	0.141***	0.115***
	[0.004]	[0.013]	[0.033]	[0.017]	[0.017]	[0.011]	[0.019]	[0.013]	[0.012]	[0.025]	[0.016]	[0.018]
Age: 35-54	0.135***	0.154***	0.055**	0.135***	0.039***	0.126***	0.071***	0.134***	0.159***	0.076***	0.189***	0.201***
	[0.003]	[0.009]	[0.028]	[0.015]	[0.015]	[0.008]	[0.013]	[0.009]	[0.008]	[0.018]	[0.013]	[0.015]
Age: 55-65	0.100***	0.120***	0.120**	0.075**	0.049*	0.093***	0.014	0.094***	0.132***	0.080	0.125***	0.133***
	[0.005]	[0.025]	[0.051]	[0.031]	[0.027]	[0.010]	[0.022]	[0.014]	[0.022]	[0.059]	[0.035]	[0.030]
Numeracy returns		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Age: 16-24		-0.054	0.083***	-0.010	0.052	0.050**	0.042***	0.047**	-0.004	-0.008	0.034	0.090***
		[0.053]	[0.019]	[0.061]	[0.040]	[0.025]	[0.016]	[0.019]	[0.035]	[0.087]	[0.031]	[0.021]
Age: 25-34		0.030	0.100***	0.038	0.057**	0.101***	0.095***	0.056***	0.049***	0.075***	0.084***	0.162***
		[0.025]	[0.017]	[0.027]	[0.023]	[0.016]	[0.011]	[0.017]	[0.019]	[0.013]	[0.019]	[0.011]
Age: 35-54		0.110***	0.165***	0.125***	0.049***	0.141***	0.122***	0.077***	0.033*	0.113***	0.168***	0.194***
		[0.014]	[0.012]	[0.017]	[0.015]	[0.010]	[0.007]	[0.021]	[0.018]	[0.011]	[0.013]	[0.009]
Age: 55-65		0.127***	0.073***	0.048	0.032	0.136***	0.085***	0.110***	0.039	0.127***	0.082***	0.179***
		[0.030]	[0.024]	[0.038]	[0.027]	[0.018]	[0.017]	[0.036]	[0.031]	[0.031]	[0.025]	[0.020]

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Horizontal lines divide separately estimated models for each age group. Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. All regressions include a constant and control also for gender and a quadratic polynomial in potential work experience (age minus years of schooling minus six). Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. Pooled specification includes country fixed effects and gives same weight to each country. Robust standard errors in square brackets. *Source*: Author's calculations & PIAAC.

Table A-7: Heterogeneity of Returns to Numeracy by Work Group

Numeracy returns	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Private sector	0.130***	0.142***	0.100***	0.097***	0.070***	0.128***	0.081***	0.125***	0.160***	0.042**	0.173***	0.178***
	[0.023]	[0.008]	[0.022]	[0.012]	[0.011]	[0.007]	[0.0011]	[0.008]	[0.007]	[0.021]	[0.011]	[0.014]
Public sector	0.107***	0.140***	0.086***	0.145***	0.031*	0.100***	0.046***	0.135***	0.153***	0.083***	0.126***	0.140***
	[0.003]	[0.013]	[0.037]	[0.018]	[0.018]	[0.008]	[0.014]	[0.009]	[0.013]	[0.022]	[0.016]	[0.016]
Full-time	0.131***	0.145***	0.114***	0.131***	0.059***	0.124***	0.069***	0.132***	0.161***	0.073***	0.183***	0.173***
	[0.002]	[0.007]	[0.020]	[0.011]	[0.010]	[0.006]	[0.009]	[0.006]	[0.007]	[0.017]	[0.010]	[0.011]
Part-time	0.102***	0.144***	0.011	0.086**	0.077*	0.082***	0.031	0.100***	0.148***	-0.009	0.092***	0.099***
	[0.005]	[0.015]	[0.051]	[0.034]	[0.046]	[0.013]	[0.054]	[0.025]	[0.016]	[0.031]	[0.021]	[0.029]
Numeracy returns		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Private sector		0.100***	0.136***	0.095***	0.074***	0.138***	0.129***	0.073***	0.055***	0.111***	0.137***	0.203***
		[0.013]	[0.010]	[0.015]	[0.015]	[0.009]	[0.007]	[0.013]	[0.014]	[0.011]	[0.012]	[0.008]
Public sector		0.096***	0.104***	0.054*	0.038***	0.135***	0.092***	0.062***	0.032*	0.102***	0.119***	0.141***
		[0.021]	[0.025]	[0.028]	[0.016]	[0.011]	[0.009]	[0.019]	[0.017]	[0.013]	[0.020]	[0.010]
Full-time		0.117***	0.138***	0.100***	0.065***	0.162***	0.114***	0.082***	0.056***	0.111***	0.167***	0.190***
		[0.012]	[0.010]	[0.014]	[0.011]	[0.008]	[0.006]	[0.010]	[0.011]	[0.008]	[0.011]	[0.007]
Part-time		0.050	0.062***	0.087*	0.0004	0.107***	0.090***	-0.018	-0.120	0.127***	0.102***	0.167***
		[0.036]	[0.016]	[0.045]	[0.051]	[0.013]	[0.013]	[0.044]	[0.102]	[0.047]	[0.022]	[0.015]

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Horizontal lines divide separately estimated models for each work group. Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. All regressions include a constant and control also for gender and a quadratic polynomial in potential work experience (age minus years of schooling minus six). Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. Pooled specification includes country fixed effects and gives same weight to each country. Robust standard errors in square brackets. *Source*: Author's calculations & PIAAC.

Table A-8: Heterogeneity of Returns to Numeracy by Societal Group

Numeracy returns	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Females	0.119***	0.154***	0.031	0.131***	0.037**	0.109**	0.056***	0.138***	0.152***	0.056***	0.185***	0.121***
	[0.003]	[0.010]	[0.030]	[0.015]	[0.017]	[0.007]	[0.013]	[0.009]	[0.009]	[0.021]	[0.014]	[0.017]
Males	0.132***	0.137***	0.140***	0.125***	0.070***	0.124***	0.073***	0.122***	0.164***	0.071***	0.167***	0.189***
	[0.003]	[0.008]	[0.025]	[0.014]	[0.011]	[0.008]	[0.012]	[0.009]	[0.009]	[0.022]	[0.013]	[0.013]
Natives	0.125***	0.136***	0.092***	0.125***	0.062***	0.116***	0.069***	0.132***	0.163***	0.067***	0.170***	0.162***
	[0.002]	[0.007]	[0.019]	[0.011]	[0.010]	[0.006]	[0.010]	[0.007]	[0.007]	[0.016]	[0.012]	[0.013]
Immigrants	0.129***	0.167***	0.250**	0.156***	0.009	0.096***	0.048**	0.078***	0.156***	0.041	0.182***	0.164***
	[0.005]	[0.018]	[0.117]	[0.026]	[0.059]	[0.011]	[0.022]	[0.025]	[0.018]	[0.064]	[0.015]	[0.020]

Numeracy returns	Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Females	0.108***	0.125***	0.051**	0.041***	0.120**	0.109***	0.043***	0.033*	0.099***	0.159***	0.182***
	[0.018]	[0.013]	[0.023]	[0.016]	[0.011]	[0.008]	[0.016]	[0.018]	[0.013]	[0.014]	[0.008]
Males	0.110***	0.144***	0.130***	0.075**	0.158***	0.118***	0.084***	0.055***	0.119***	0.160***	0.204***
	[0.015]	[0.012]	[0.016]	[0.015]	[0.009]	[0.007]	[0.014]	[0.015]	[0.010]	[0.013]	[0.010]
Natives	0.109***	0.140***	0.097***	0.062***	0.137***	0.110***	0.071***	0.049***	0.119***	0.163***	0.191***
	[0.013]	[0.009]	[0.014]	[0.011]	[0.008]	[0.007]	[0.011]	[0.012]	[0.009]	[0.011]	[0.007]
Immigrants	0.058**	-	0.122**	0.046	0.476***	0.109***	-	-0.150**	0.046**	0.096***	0.212***
	[0.029]	-	[0.046]	[0.039]	[0.019]	[0.009]	-	[0.066]	[0.023]	[0.029]	[0.016]

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Horizontal lines divide separately estimated models for each societal group. Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. All regressions include a constant and control also for gender (except males and females which estimated separately for each sub-sample) and a quadratic polynomial in potential work experience (age minus years of schooling minus six). Observations for immigrant workers in Japan and Poland were too few and returns to numeracy cannot be estimated. Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. Pooled specification includes country fixed effects and gives same weight to each country. Robust standard errors in square brackets. *Source*: Author's calculations & PIAAC.

Table A-9: Why Tasks Add Value in the Empirical Analysis?

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Numeracy	0.094***	0.094***	0.089***	0.088***	0.077***	0.056***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Experience	0.025***	0.024***	0.024***	0.024***	0.022***	0.021***
	[0.001]	[0.001]	[0.001]	[0.0007]	[0.001]	[0.001]
Experience^2	-0.037***	-0.035***	-0.035***	-0.035***	-0.033***	-0.031***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Female	-0.103***	-0.095***	-0.094***	-0.091***	-0.106***	-0.095***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
ICT	0.081***	0.069***	0.063***	0.056***	0.050***	0.034***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Influence		0.053***	0.054***	0.051***	0.048***	0.029***
		[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Physical			-0.040***	-0.039***	-0.036***	-0.27***
			[0.002]	[0.002]	[0.002]	[0.002]
Discretion				0.29***	0.035***	0.028***
				[0.002]	[0.002]	[0.002]
Country fixed effects	X	X	X	X	X	X
Industry fixed effects (22)					X	X
Occupation fixed effects (10)						X
R^2	0.42	0.43	0.44	0.44	0.46	0.50
Observations	35,226	34,221	34,196	33,776	33,398	33,037

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions pooling all countries with country fixed effects, weighted by sampling weights (giving same weight to each country). Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. Numeracy scores standardised to within-country mean of 0 and standard deviation of 1. Job tasks (*ICT*; *Influence*; *Physical*; *Discretion*) frequency/intensity are standardised to within-country mean of 2 and standard deviation of 1. *Female* is a binary gender indicator and *Experience* refers to the potential experience (age minus years of schooling minus six). *Experience*^{2} is divided by 100. Number in parentheses reports the number of occupation and industry fixed effects. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported. *Source*: Author's calculations & PIAAC.

Table A-10: Task-based Approach

Variables	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Numeracy	0.088***	0.081***	0.103***	0.127***	0.043***	0.073***	0.049***	0.079***	0.120***	0.046**	0.122***	0.138***
	[0.002]	[0.010]	[0.025]	[0.014]	[0.012]	[0.006]	[0.011]	[0.007]	[0.010]	[0.021]	[0.013]	[0.015]
Experience	0.024***	0.030***	0.003	0.027***	0.010***	0.023***	0.012***	0.023***	0.022***	0.012	0.033***	0.036***
	[0.0007]	[0.0024]	[0.0071]	[0.0042]	[0.0033]	[0.0020]	[0.0033]	[0.0022]	[0.0024]	[0.0114]	[0.0034]	[0.0045]
Experience^2	-0.035***	-0.039***	0.001	-0.027**	-0.022***	-0.035***	-0.026***	-0.033***	-0.025***	0.004	-0.055***	-0.049***
	[0.001]	[0.006]	[0.016]	[0.011]	[0.008]	[0.004]	[0.007]	[0.005]	[0.006]	[0.028]	[0.009]	[0.010]
Female	-0.091***	-0.024	-0.061	-0.032	-0.082***	-0.057***	-0.221***	-0.133***	-0.080***	-0.012	-0.029***	-0.074***
	[0.002]	[0.009]	[0.021]	[0.014]	[0.012]	[0.006]	[0.012]	[0.007]	[0.009]	[0.021]	[0.010]	[0.014]
ICT	0.056***	0.017*	0.072***	0.006	0.034***	0.079***	0.039***	0.081***	0.060***	0.022	0.037***	0.071***
	[0.002]	[0.009]	[0.021]	[0.014]	[0.012]	[0.006]	[0.012]	[0.007]	[0.009]	[0.021]	[0.010]	[0.014]
Influence	0.051***	0.025***	0.043*	0.135***	0.034***	0.022***	0.022***	0.056***	0.046***	0.060***	0.102***	0.036***
	[0.002]	[0.008]	[0.022]	[0.014]	[0.013]	[0.005]	[0.011]	[0.007]	[0.008]	[0.021]	[0.010]	[0.013]
Physical	-0.038***	-0.048***	-0.086***	-0.039***	-0.031***	-0.046	-0.007	-0.054***	-0.050***	-0.070***	-0.047***	-0.042***
	[0.002]	[0.008]	[0.021]	[0.013]	[0.011]	[0.005]	[0.010]	[0.007]	[0.008]	[0.023]	[0.010]	[0.012]
Discretion	0.029***	0.018**	0.026	0.002	0.032***	0.021***	0.064***	0.010***	0.021***	0.032	0.018*	0.032***
	[0.002]	[0.009]	[0.021]	[0.014]	[0.012]	[0.005]	[0.012]	[0.007]	[0.008]	[0.023]	[0.010]	[0.014]
R^2	0.44	0.28	0.13	0.24	0.090	0.29	0.16	0.35	0.27	0.14	0.25	0.26
Observations	33,776	1,719	652	1,145	1,096	3,165	1,531	2,352	2,094	443	1,669	1,169

Variables		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Numeracy		0.065***	0.096***	0.082***	0.026*	0.081***	0.074***	0.055***	0.052***	0.095***	0.120***	0.129***
		[0.017]	[0.011]	[0.017]	[0.015]	[0.009]	[0.006]	[0.013]	[0.016]	[0.011]	[0.016]	[0.008]
Experience		0.024***	0.033***	0.023***	0.005	0.032***	0.022***	0.023***	-0.005	0.012**	0.024***	0.032***
		[0.005]	[0.003]	[0.005]	[0.005]	[0.002]	[0.002]	[0.004]	[0.005]	[0.005]	[0.004]	[0.002]
Experience^2		-0.026***	-0.046***	0.022*	-0.006	-0.047***	-0.037***	-0.042***	0.012	-0.008	-0.031***	-0.055***
		[0.010]	[0.007]	[0.012]	[0.028]	[0.005]	[0.004]	[0.009]	[0.011]	[0.011]	[0.009]	[0.005]
Female		-0.004	-0.254***	-0.097***	-0.117***	-0.046***	-0.107***	-0.040*	-0.110***	-0.018	-0.059***	-0.093***
		[0.026]	[0.020]	[0.029]	[0.012]	[0.015]	[0.011]	[0.023]	[0.027]	[0.019]	[0.024]	[0.014]
ICT		0.007	0.091***	0.061***	0.064***	0.060***	0.063***	0.015	0.033**	0.037***	0.028**	0.092***
		[0.014]	[0.011]	[0.014]	[0.016]	[0.008]	[0.006]	[0.011]	[0.014]	[0.011]	[0.013]	[0.008]
Influence		0.110***	0.056***	0.057***	0.034**	0.041***	0.020***	0.034***	0.042***	0.031***	0.095***	0.072***
		[0.013]	[0.010]	[0.014]	[0.014]	[0.007]	[0.005]	[0.011]	[0.015]	[0.009]	[0.011]	[0.007]
Physical		-0.029**	-0.021**	-0.005	-0.004	-0.052***	-0.035***	-0.042***	-0.047***	-0.024**	-0.045***	-0.035***
		[0.013]	[0.009]	[0.014]	[0.014]	[0.007]	[0.006]	[0.012]	[0.015]	[0.010]	[0.012]	[0.007]
Discretion		0.060***	0.014	0.023	0.029***	0.033***	0.014**	0.041***	0.036**	0.018*	0.036***	0.040***
		[0.013]	[0.010]	[0.014]	[0.016]	[0.008]	[0.006]	[0.014]	[0.016]	[0.010]	[0.012]	[0.008]
R^2		0.21	0.34	0.14	0.090	0.32	0.31	0.14	0.11	0.16	0.22	0.32
Observations		957	1,892	1,527	750	2,060	2,676	1,016	716	995	1,118	3,034

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: employees aged 16-65. Numeracy scores standardized to within-country mean of 0 and standard deviation of 1. Tasks (*ICT*; *Influence*; *Physical*; *Discretion*) frequency/intensity are standardised to within-country mean of 2 and standard deviation of 1. *Female* is a binary gender indicator and *Experience* refers to the potential experience (age minus years of schooling minus six). *Experience*^{2} is divided by 100. Pooled specification includes country fixed effects and gives same weight to each country. Number in parentheses reports the number of occupation and industry fixed effects. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported. *Source*: Author's calculations & PIAAC.

Table A-11: Task-based Approach; Robustness Check

Variables	Pooled	Belgium	Chile	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Greece	Ireland	Israel
Numeracy	0.091***	0.090***	0.043	0.131***	0.037**	0.075***	0.053***	0.085***	0.111***	0.042	0.127***	0.143***
	[0.004]	[0.016]	[0.038]	[0.021]	[0.017]	[0.010]	[0.015]	[0.011]	[0.014]	[0.026]	[0.018]	[0.021]
Experience	0.0005	0.012	-0.003	-0.039*	-0.013	-0.005	-0.028	-0.004	0.003	0.068**	0.014***	-0.011
	[0.003]	[0.013]	[0.041]	[0.021]	[0.016]	[0.008]	[0.020]	[0.009]	[0.010]	[0.028]	[0.014]	[0.023]
Experience^2	0.003	-0.008	-0.020**	-0.095	0.012	0.006	0.052	0.007	0.001	-0.127***	-0.021	0.034
	[0.006]	[0.026]	[0.087]	[0.047]	[0.034]	[0.016]	[0.041]	[0.017]	[0.019]	[0.062]	[0.034]	[0.047]
Female	-0.107***	-0.056**	-0.153**	-0.113***	-0.133***	-0.086***	-0.290***	-0.168***	-0.099***	0.006	0.026	-0.077***
	[0.006]	[0.025]	[0.066]	[0.042]	[0.031]	[0.014]	[0.029]	[0.017]	[0.022]	[0.048]	[0.028]	[0.036]
ICT	0.063***	0.047***	0.086***	-0.013	0.031*	0.074***	0.064***	0.085***	0.067***	0.045*	0.043***	0.087***
	[0.003]	[0.014]	[0.031]	[0.022]	[0.018]	[0.008]	[0.017]	[0.009]	[0.012]	[0.027]	[0.016]	[0.020]
Influence	0.050***	0.020	0.025	0.128***	0.020	0.021***	0.004	0.047***	0.041***	0.062**	0.084***	0.034**
	[0.003]	[0.012]	[0.032]	[0.021]	[0.016]	[0.008]	[0.014]	[0.008]	[0.011]	[0.025]	[0.015]	[0.017]
Physical	-0.044***	-0.056***	-0.114***	-0.033	-0.015	-0.050***	0.006	-0.055***	-0.060***	-0.065**	-0.063***	-0.067***
	[0.003]	[0.012]	[0.032]	[0.020]	[0.016]	[0.007]	[0.014]	[0.009]	[0.011]	[0.028]	[0.014]	[0.018]
Discretion	0.026***	0.008	0.005	0.030	0.032*	0.032***	0.065***	0.010	0.009	0.010	0.016	0.037*
	[0.003]	[0.013]	[0.032]	[0.022]	[0.018]	[0.008]	[0.015]	[0.009]	[0.011]	[0.025]	[0.015]	[0.020]
R^2	0.46	0.17	0.17	0.18	0.12	0.29	0.22	0.36	0.22	0.10	0.19	0.22
Observations	15,589	734	280	538	471	1,364	742	1,144	1,038	306	767	533

Variables		Italy	Japan	Korea	Lithuania	Netherlands	Norway	Poland	Slovak R.	Slovenia	Spain	U.K.
Numeracy		0.053**	0.112***	0.111***	0.031	0.102***	0.065***	0.084***	0.046**	0.090***	0.126***	0.121***
		[0.021]	[0.016]	[0.022]	[0.019]	[0.014]	[0.009]	[0.021]	[0.021]	[0.014]	[0.023]	[0.012]
Experience		0.009	0.007	-0.019	-0.010	-0.006	0.012	0.006	-0.029	0.019	0.030*	0.008
		[0.016]	[0.015]	[0.018]	[0.025]	[0.014]	[0.009]	[0.028]	[0.021]	[0.018]	[0.016]	[0.012]
Experience^2		-0.016	0.010	0.059	0.015	0.018	-0.026	-0.017	0.051	-0.030	-0.062*	-0.018
		[0.033]	[0.032]	[0.039]	[0.055]	[0.028]	[0.020]	[0.059]	[0.046]	[0.034]	[0.032]	[0.025]
Female		-0.025	-0.198***	-0.158***	-0.178***	0.014	-0.124***	-0.015	-0.152***	-0.018	-0.041	-0.127
		[0.033]	[0.029]	[0.042]	[0.041]	[0.033]	[0.015]	[0.041]	[0.036]	[0.025]	[0.033]	[0.022]
ICT		0.022	0.084***	0.080***	0.073***	0.051***	0.067***	0.019	0.042**	0.053***	0.041**	0.090***
		[0.018]	[0.015]	[0.020]	[0.020]	[0.015]	[0.009]	[0.022]	[0.020]	[0.014]	[0.019]	[0.012]
Influence		0.112***	0.047***	0.064***	0.050**	0.037***	0.026***	0.048**	0.049**	0.056***	0.084***	0.066***
		[0.015]	[0.013]	[0.018]	[0.020]	[0.014]	[0.007]	[0.019]	[0.020]	[0.012]	[0.014]	[0.011]
Physical		-0.027*	-0.026*	0.008	-0.007	-0.070***	-0.053***	-0.049***	-0.067***	-0.033***	-0.051***	-0.037***
		[0.016]	[0.014]	[0.018]	[0.017]	[0.012]	[0.008]	[0.023]	[0.021]	[0.014]	[0.016]	[0.012]
Discretion		0.048	0.012	0.011	0.018	0.042***	0.005	0.056***	0.048**	0.011	0.025	0.046***
		[0.017]	[0.014]	[0.017]	[0.022]	[0.013]	[0.008]	[0.008]	[0.023]	[0.014]	[0.016]	[0.012]
R^2		0.15	0.25	0.14	0.16	0.23	0.28	0.12	0.19	0.17	0.18	0.27
Observations		560	894	749	360	657	1,284	330	353	608	625	1,252

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Least squares regressions weighted by sampling weights. Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: full-time employees aged 35-54. Numeracy scores standardized to within-country mean of 0 and standard deviation of 1. Tasks (*ICT*; *Influence*; *Physical*; *Discretion*) frequency/intensity are standardised to within-country mean of 2 and standard deviation of 1. *Female* is a binary gender indicator and *Experience* refers to the potential experience (age minus years of schooling minus six). *Experience*^{2} is divided by 100. Pooled specification includes country fixed effects and gives same weight to each country. Number in parentheses reports the number of occupation and industry fixed effects. R^2 refers to within-country R^2. Robust standard errors in square brackets. The constant was estimated but not reported. *Source*: Author's calculations & PIAAC.

Table A-12: Data for Cross-Country Characteristics

Country	Round	EPL	Unionism	GDP per capita Growth	Productivity Growth	Minimum Wage	Public Sector	R&D Investments
Belgium	1	2.08	55.1%	1.1%	0.7%	Yes	32%	2.0%
Chile	2	2.63	15.0%	4.1%	0.5%	Yes	21%	0.3%
Cyprus	1	-	-	0.9%	-	No	39%	0.4%
Czech Republic	1	3.05	12.7%	1.1%	2.6%	Yes	35%	1.4%
Denmark	1	2.13	66.8%	-0.2%	0.5%	No	37%	2.9%
Estonia	1	1.81	5.7%	0.3%	0.2%	Yes	35%	1.6%
Finland	1	2.17	69.0%	0.3%	1.6%	Yes	38%	3.6%
France	1	2.38	7.7%	0.6%	-0.6%	Yes	29%	2.1%
Greece	2	2.12	21.5%	-3.9%	0.3%	Yes	55%	0.6%
Ireland	1	1.27	29.6%	-0.7%	0.6%	Yes	39%	1.5%
Israel	2	2.04	22.8%	3.9%	2.9%	Yes	41%	4.2%
Italy	1	2.76	37.3%	-0.9%	0.9%	No	34%	1.2%
Japan	2	1.37	17.8%	0.1%	-0.3%	Yes	17%	3.4%
Korea	1	2.37	10.1%	3.6%	0.9%	Yes	22%	3.4%
Lithuania	2	2.45	-	1.7%	-	Yes	42%	0.8%
Netherlands	1	2.82	17.8%	0.6%	0.0%	Yes	29%	1.8%
Norway	1	2.33	52.1%	1.0%	1.0%	Yes	37%	1.6%
Poland	1	2.33	12.7%	4.1%	-0.4%	Yes	51%	0.7%
Slovak Republic	1	2.22	13.3%	3.4%	1.5%	Yes	39%	0.6%
Slovenia	2	2.60	21.2%	0.3%	1.7%	Yes	44%	2.0%
Spain	1	2.36	16.9%	-0.4%	1.2%	Yes	34%	1.3%
United Kingdom	1	1.26	25.8%	0.4%	0.1%	Yes	40%	1.7%
Pooled Sample	-	2.21	26.5%	1.0%	0.8%	-	35%	1.8%
Num. of Countries	22	21	20	22	20	22	22	22

Round 1 of PIAAC, administered between August 2011 and March 2012. *Round 2* of PIAAC, administered between April 2014 and March 2015. *EPL*: Employment Protection Legislation is a composite indicator measuring strictness of employment protection for individual and collective dismissals. 2010 EPL index for *Round 1* countries and 2013 EPL for *Round 2* countries. *Unionism*: share of workers who are trade union members. 2010 labour union membership for *Round 1* countries and 2013 labour union membership *Round 2* countries. *GDP per capita Growth*: Average GDP per capita percentage growth (2007-2012). *Productivity*: Average percentage change in workers' real productivity (2007-2012). *Minimum Wage*: binary variable indicating whether country has a statutory minimum wage. *Public Sector*: share of workers employed in the public sector. *R&D Investments*: Average gross domestic expenditure on R&D (GERD) as percentage of GDP (2007-2012). Sample: full-time employees aged 35-54. *Source*: OECD, PIAAC & World Bank.

Table A-13: What Cross-Country Characteristics Affect Returns to Numeracy?

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numeracy	0.133***	0.135***	0.132***	0.135***	0.135***	0.144***	0.135***	0.147***	0.077***
	[0.008]	[0.010]	[0.009]	[0.009]	[0.005]	[0.01]	[0.009]	[0.009]	[0.006]
× *EPL*	-0.045***							-0.039**	-0.035**
	[0.013]							[0.02]	[0.014]
× *Unionism*		0.0002							
		[0.0003]							
× *GDP per capita Growth*			-0.003						
			[0.006]						
× *Productivity Growth*				-0.008					
				[0.013]					
× *Minimum Wage*					-0.004				
					[0.0013]				
× *Public Sector*						-0.034***		-0.036***	-0.021***
						[0.008]		[0.009]	[0.006]
× *R&D Investements*							0.016**	0.013*	0.010
							[0.007]	[0.007]	[0.006]
Country fixed effects	X	X	X	X	X	X	X	X	X
Industry fixed effects (22)									X
Occupation fixed effects (10)									X
R^2	0.42	0.41	0.41	0.41	0.41	0.41	0.41	0.42	0.51
Number of Countries	21	20	22	20	22	22	22	21	21
Observations	20,299	19,761	21,217	19,761	21,217	21,217	21,217	20,299	20,299

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

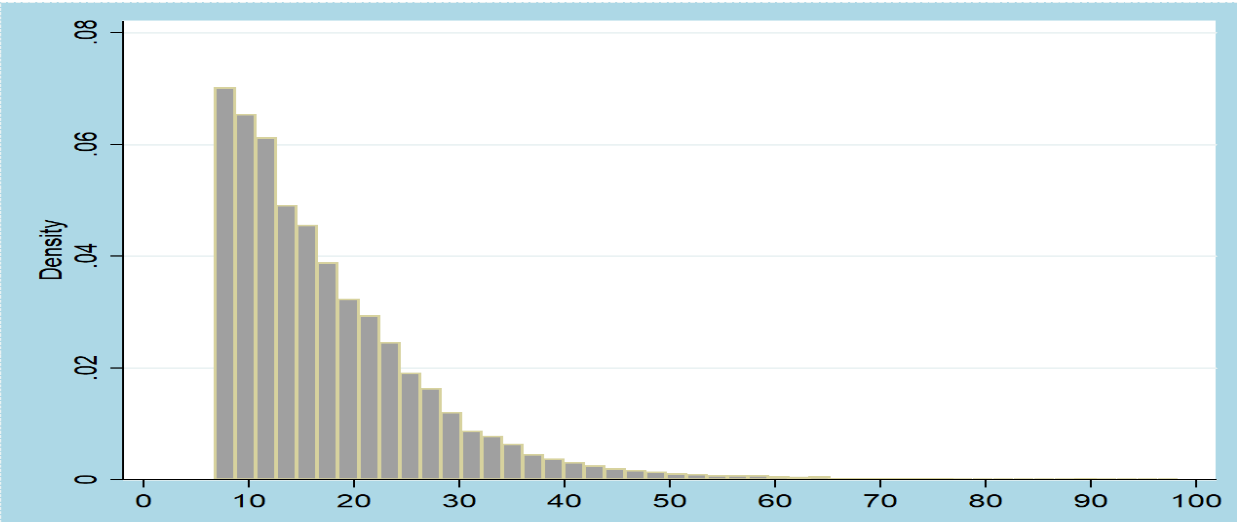
Notes: Least squares regressions pooling all countries with country fixed effects, weighted by sampling weights (giving same weight to each country). Dependent variable: Log Gross Hourly Earnings (in PPP U.S. dollars). Sample: full-time employees aged 35-54. All regressions control also for gender, a quadratic polynomial in potential work experience (age minus years of schooling minus six) and country fixed effects. Numeracy scores standardized to within-country mean of 0 and standard deviation of 1. All interaction variables are de-meaned except *Minimum Wage*. *EPL*: Employment Protection Legislation is a composite indicator measuring strictness of employment protection for individual and collective dismissals. *Unionism*: share of workers who are trade union members. *GDP per capita Growth*: Average GDP per capita growth (2007-2012) . *Productivity Growth*: Average real percentage change in workers' productivity. *Minimum Wage*: binary variable indicating whether country has a statutory minimum wage. *Public Sector*: share of workers employed in the public sector. *R&D Investments*: Gross domestic expenditure on R&D (GERD) as percentage of GDP. Number in parentheses reports the number of occupation and industry fixed effects. Due to missing data, Cyprus is included only in columns (3), (5), (6) and (7). Similarly, Lithuania is not included in columns (2) and (4). R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at country level) in square brackets. The constant was estimated but not reported. *Source*: OECD, PIAAC & World Bank.

Table A-14: Country Acronyms in Figures

Country	Acronym
Belgium	BEL
Chile	CHL
Cyprus	CYP
Czech Republic	CZE
Denmark	DNK
Estonia	EST
Finland	FIN
France	FRA
Greece	GRC
Ireland	IRL
Israel	ISR
Italy	ITA
Japan	JPN
Korea	KOR
Lithuania	LTU
Netherlands	NLD
Norway	NOR
Poland	POL
Slovak Republic	SVK
Slovenia	SVN
Spain	ESP
United Kingdom	UK
International Sample	Pooled

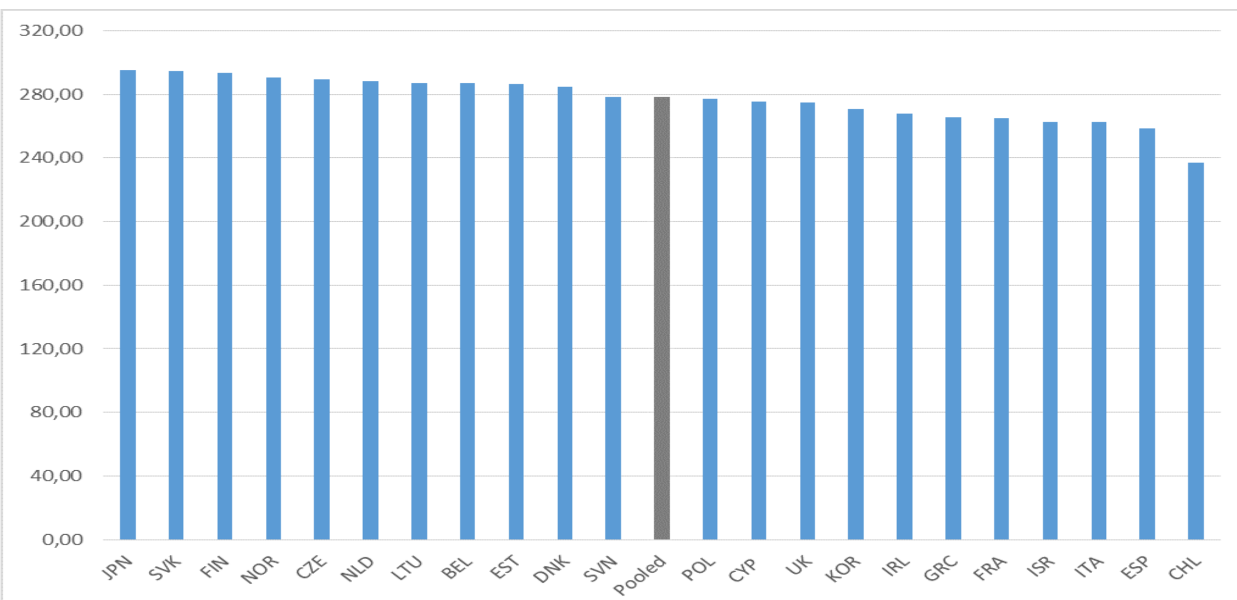
Appendix B: Figures

Figure A-1: Hourly Wage Distribution (in PPP US$); Pooled Sample



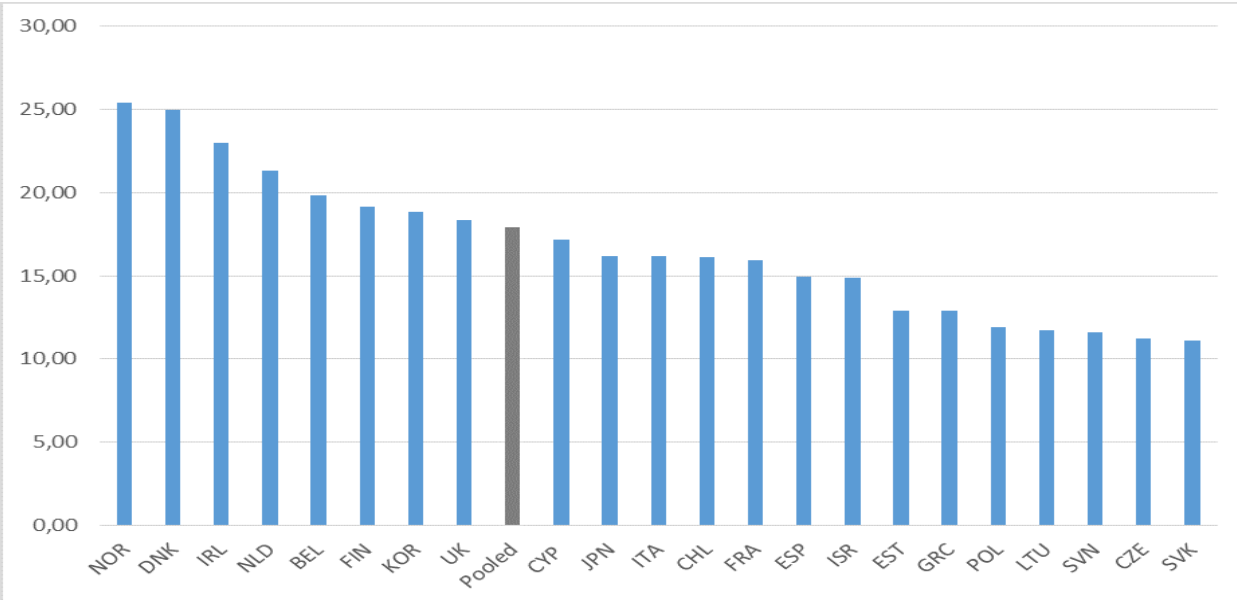
Source: PIAAC.

Figure A-2: Average Numeracy Scores by Country



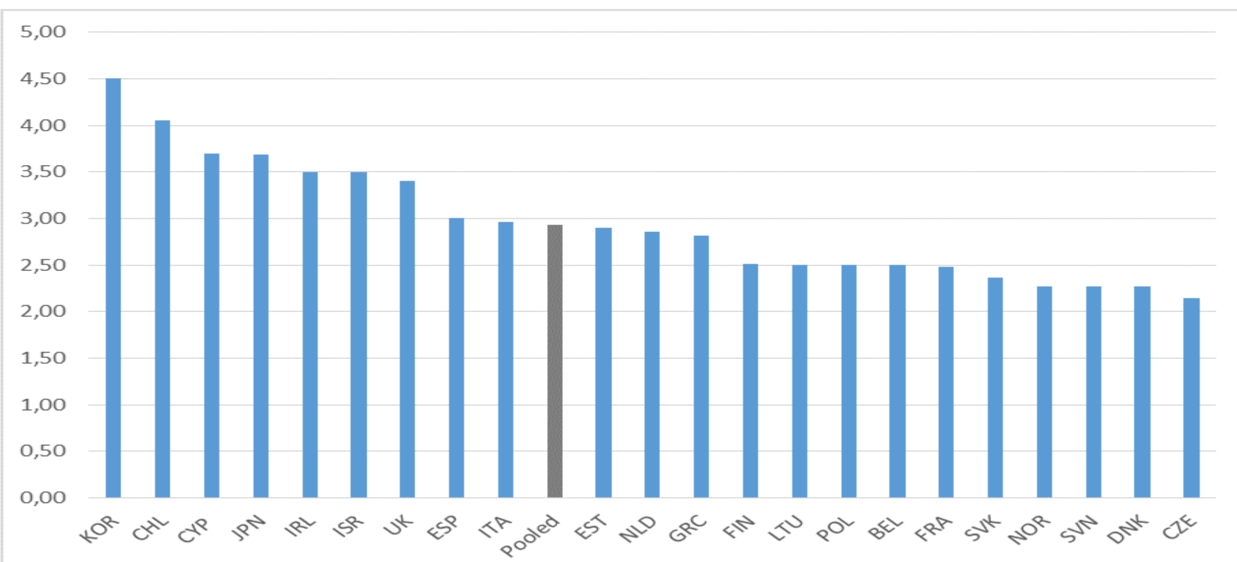
Note: Country acronyms can be found in Table A-14. *Source*: PIAAC.

Figure A-3: Average Gross Hourly Wage (PPP in U.S.$) by Country



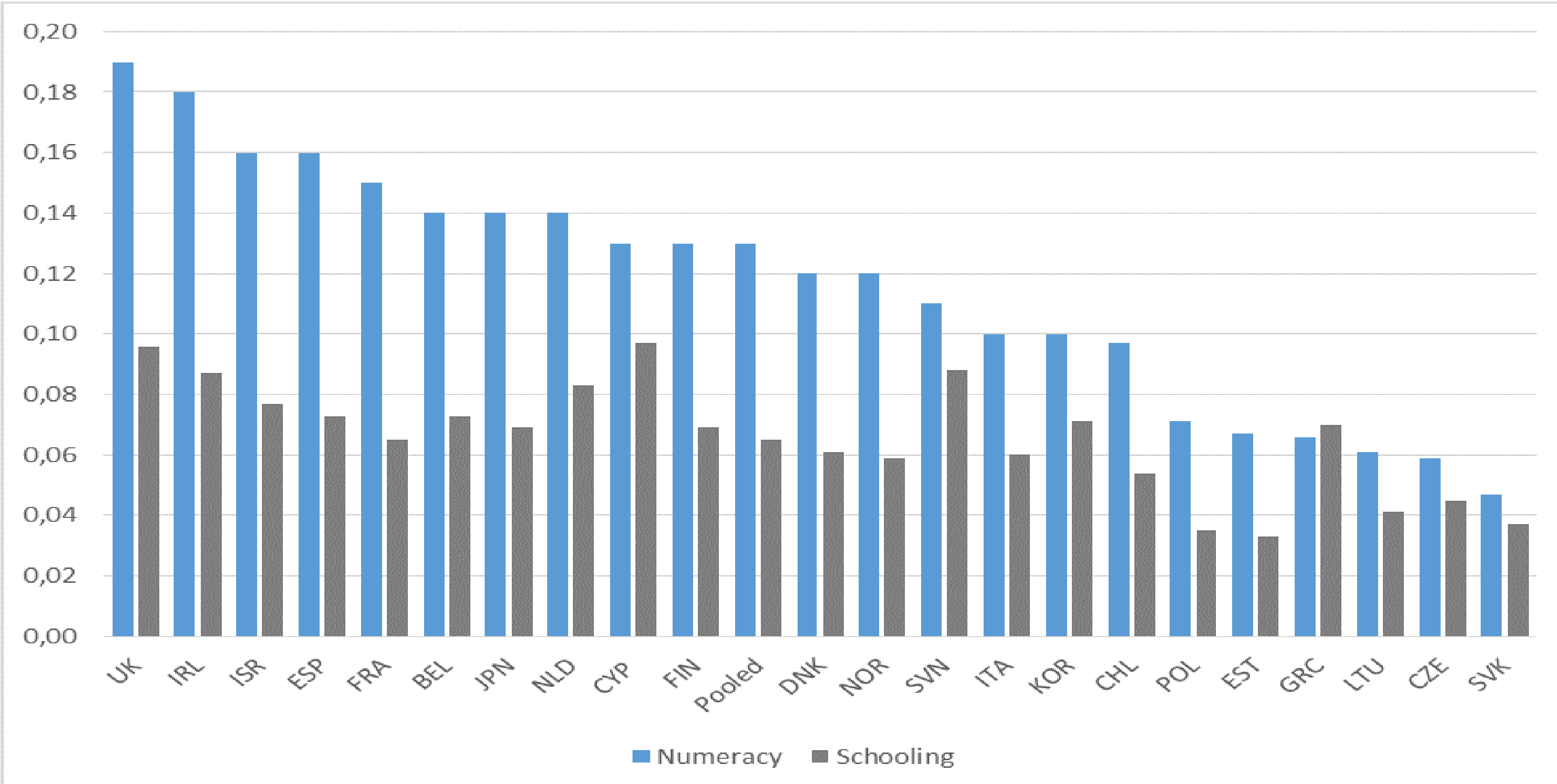
Note: Country acronyms can be found in Table A-14. *Source*: PIAAC.

Figure A-4: Wage Inequality by Country



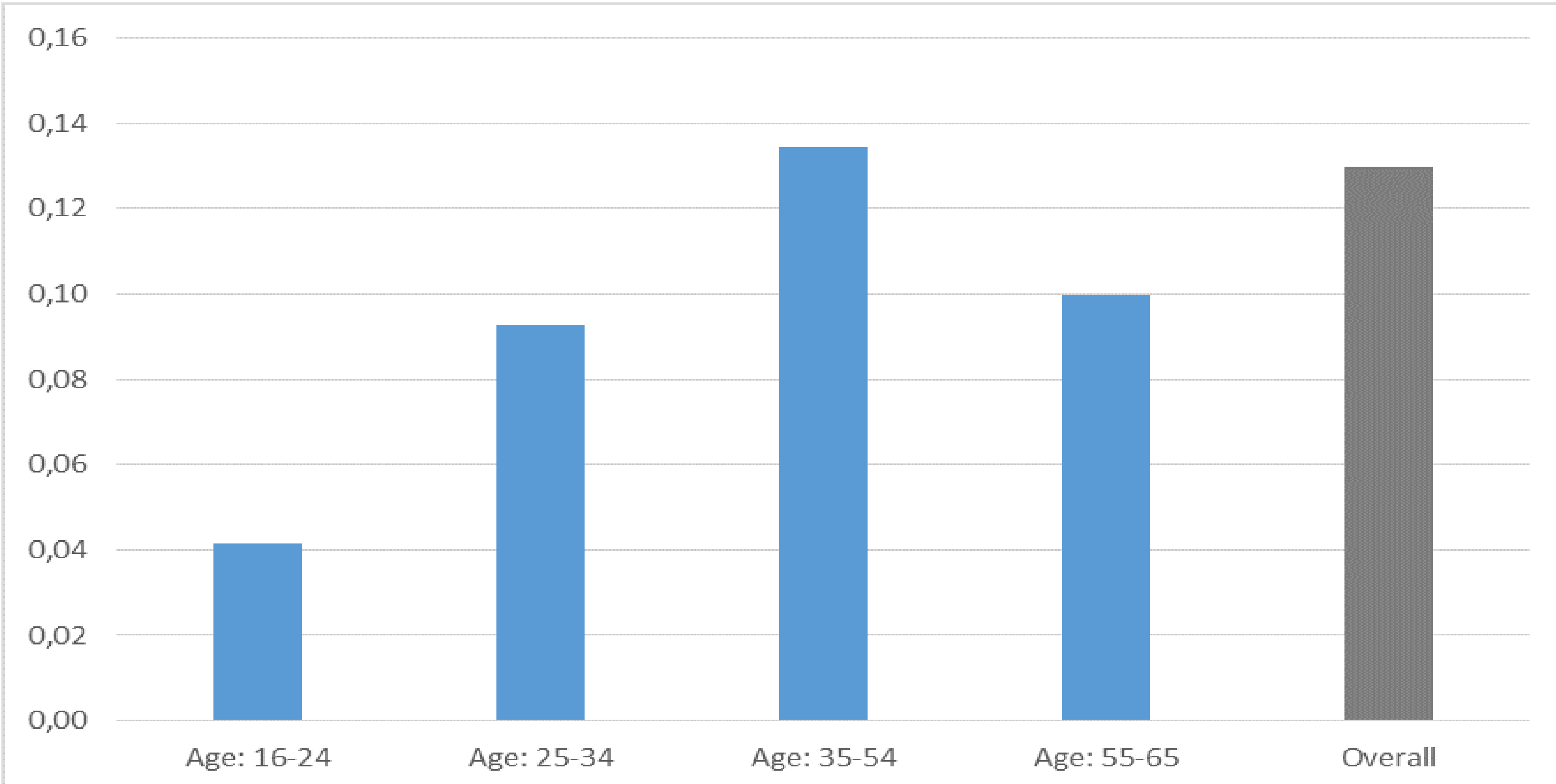
Notes: Wage inequality defined as gross hourly wage ratio between 90th and 10th percentile of wage distribution. Country acronyms can be found in Table A-14. *Source*: PIAAC.

Figure A-5: Comparison of Returns to Numeracy and Schooling



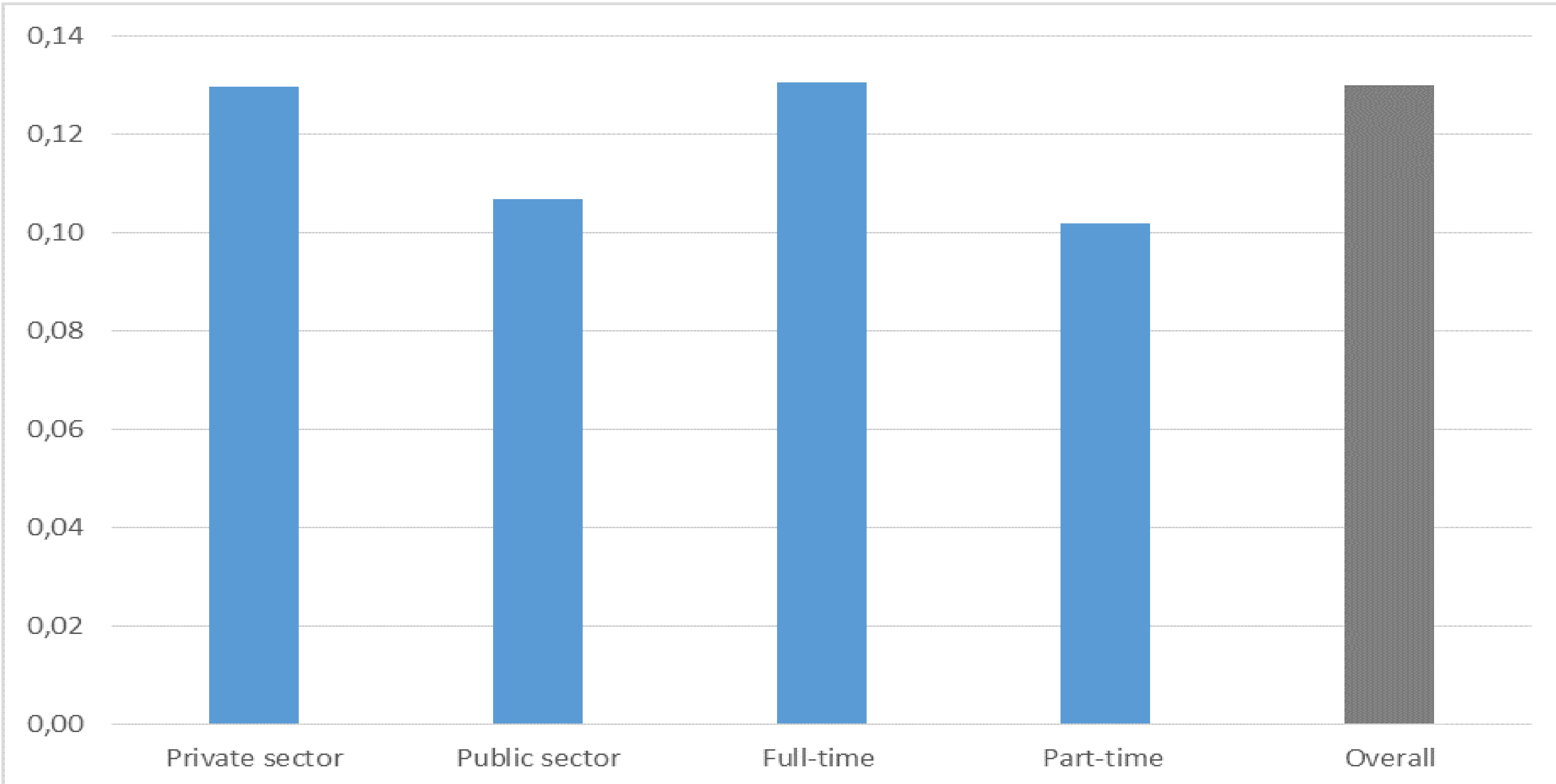
Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) and schooling (defined as the highest level of school attainment) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy/schooling, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six). Sample: employees aged 16-65. Returns to numeracy and schooling are statistically significant at 1 percent level. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-2 and Table A-3. Table A-4 presents the precise differences in numeracy and schooling estimated rates of returns. Country acronyms can be found in Table A-14. *Source*: Author's calculations & PIAAC.

Figure A-6: Age Varying Returns to Numeracy; Pooled Sample



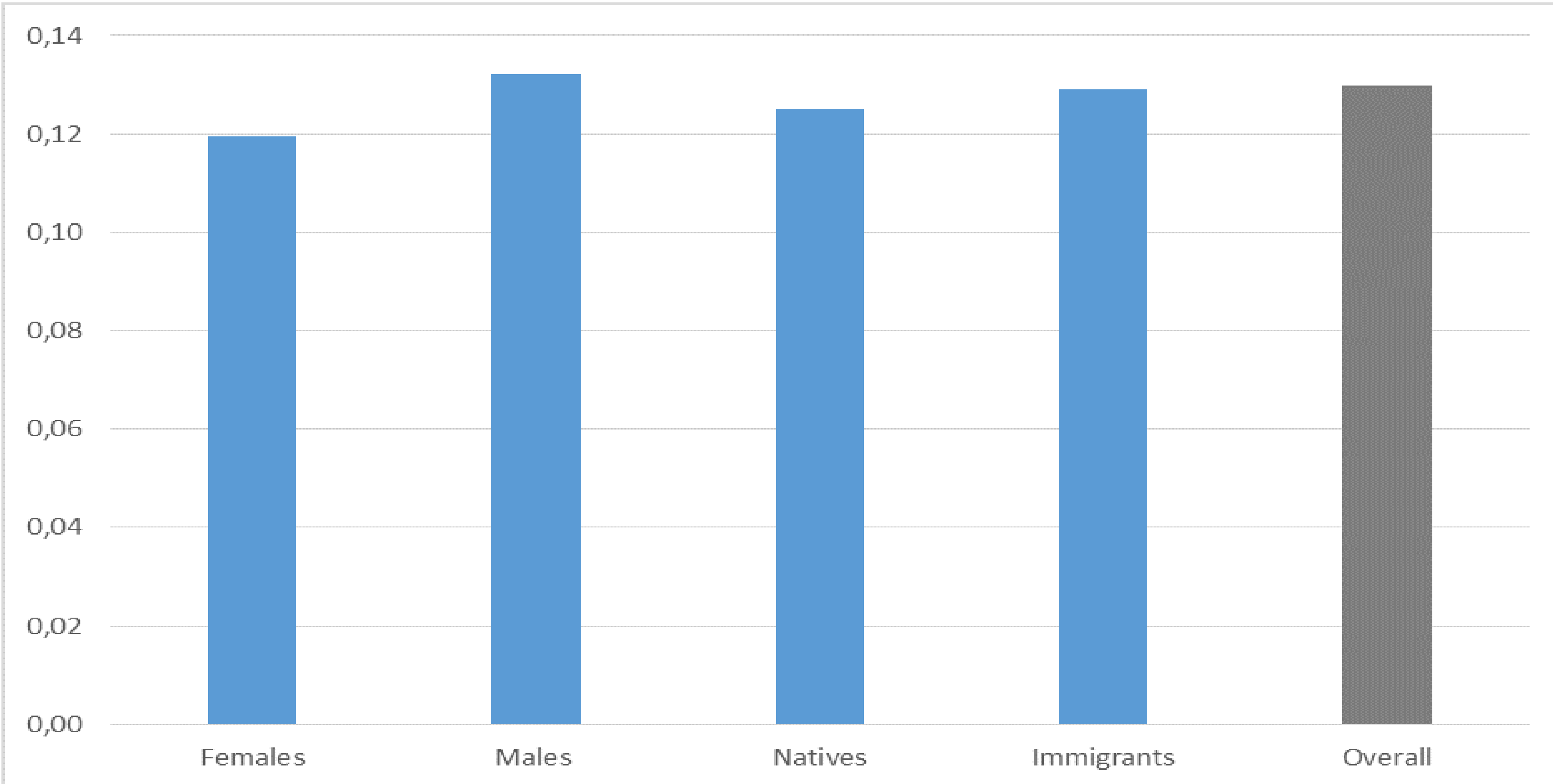
Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six) estimated for each age group separately. Pooled Sample: international employees aged 16-65. Returns to numeracy are statistically significant at 1 percent level for every age group. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-6. *Source*: Author's calculations & PIAAC.

Figure A-7: Numeracy Returns by Different Work Sub-groups; Pooled Sample



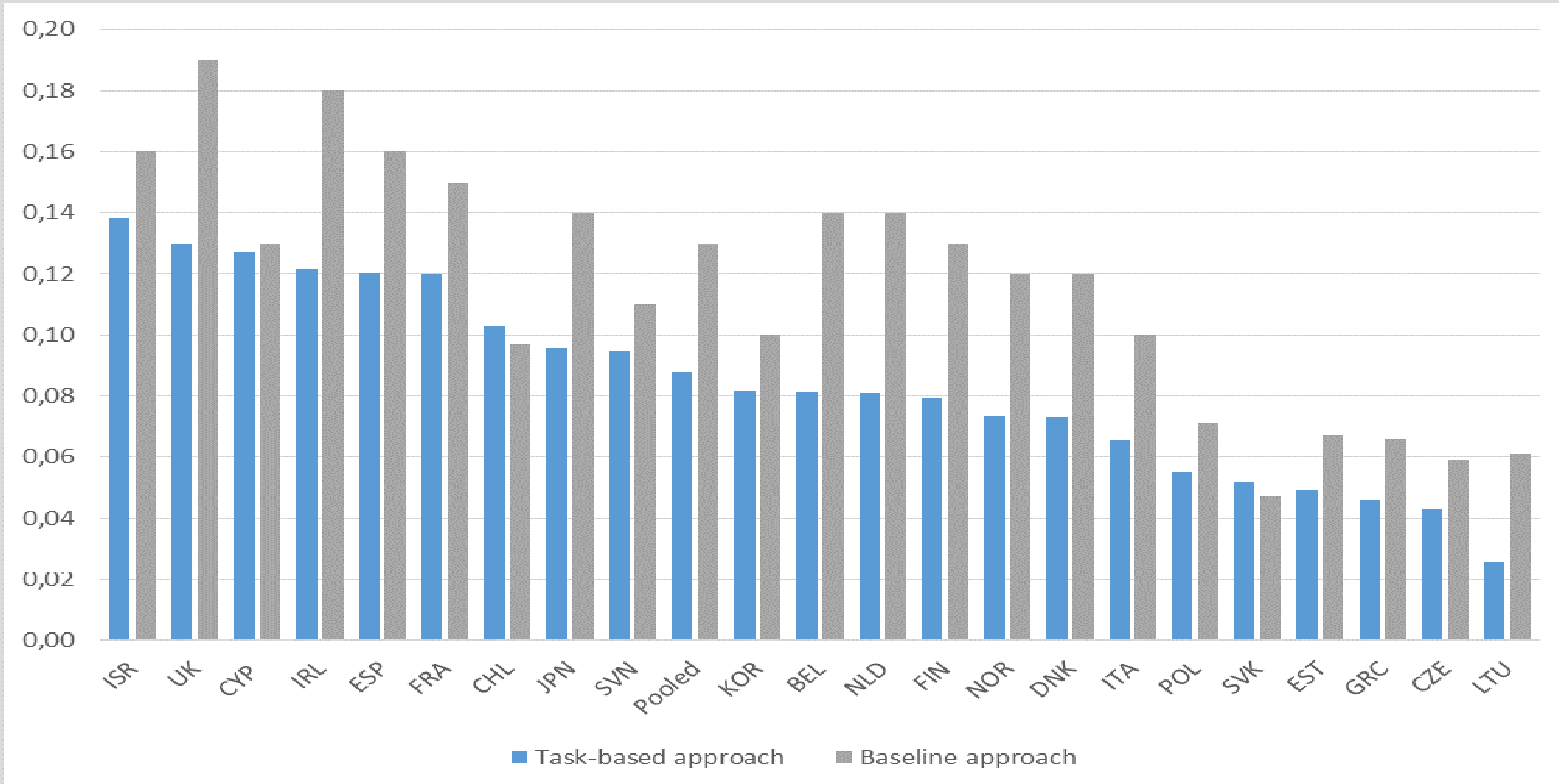
Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six) estimated for each work group separately. Pooled Sample: international employees aged 16-65. Returns to numeracy are statistically significant at 1 percent level for every work group. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-7. *Source*: Author's calculations & PIAAC.

Figure A-8: Numeracy Returns by Different Societal Sub-groups; Pooled Sample



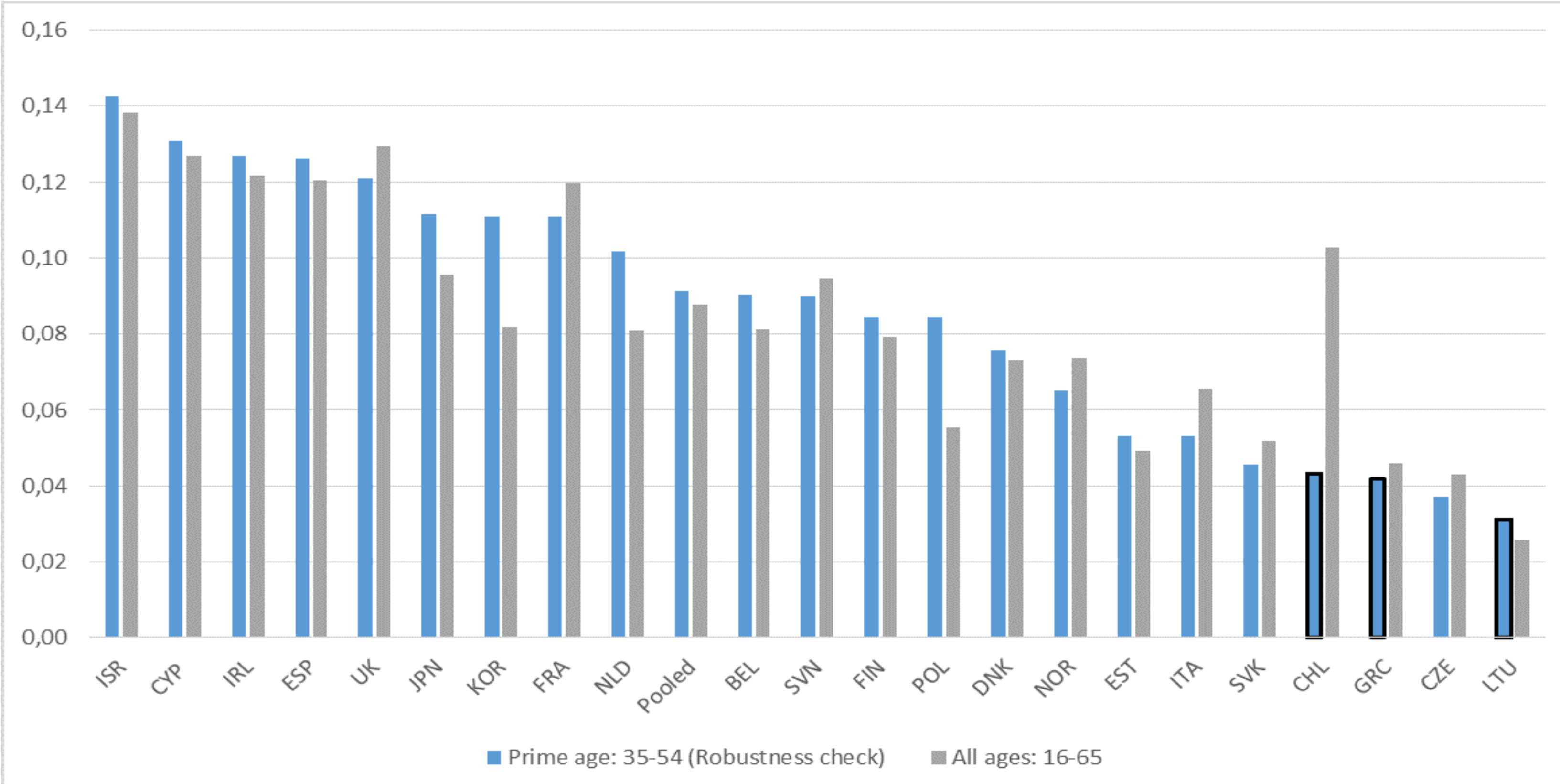
Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six) estimated for each societal group separately. Pooled Sample: international employees aged 16-65. Returns to numeracy are statistically significant at 1 percent level for every societal group. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-8. *Source*: Author's calculations & PIAAC.

Figure A-9: Returns to Numeracy; Comparison of Baseline and Task-based Approach



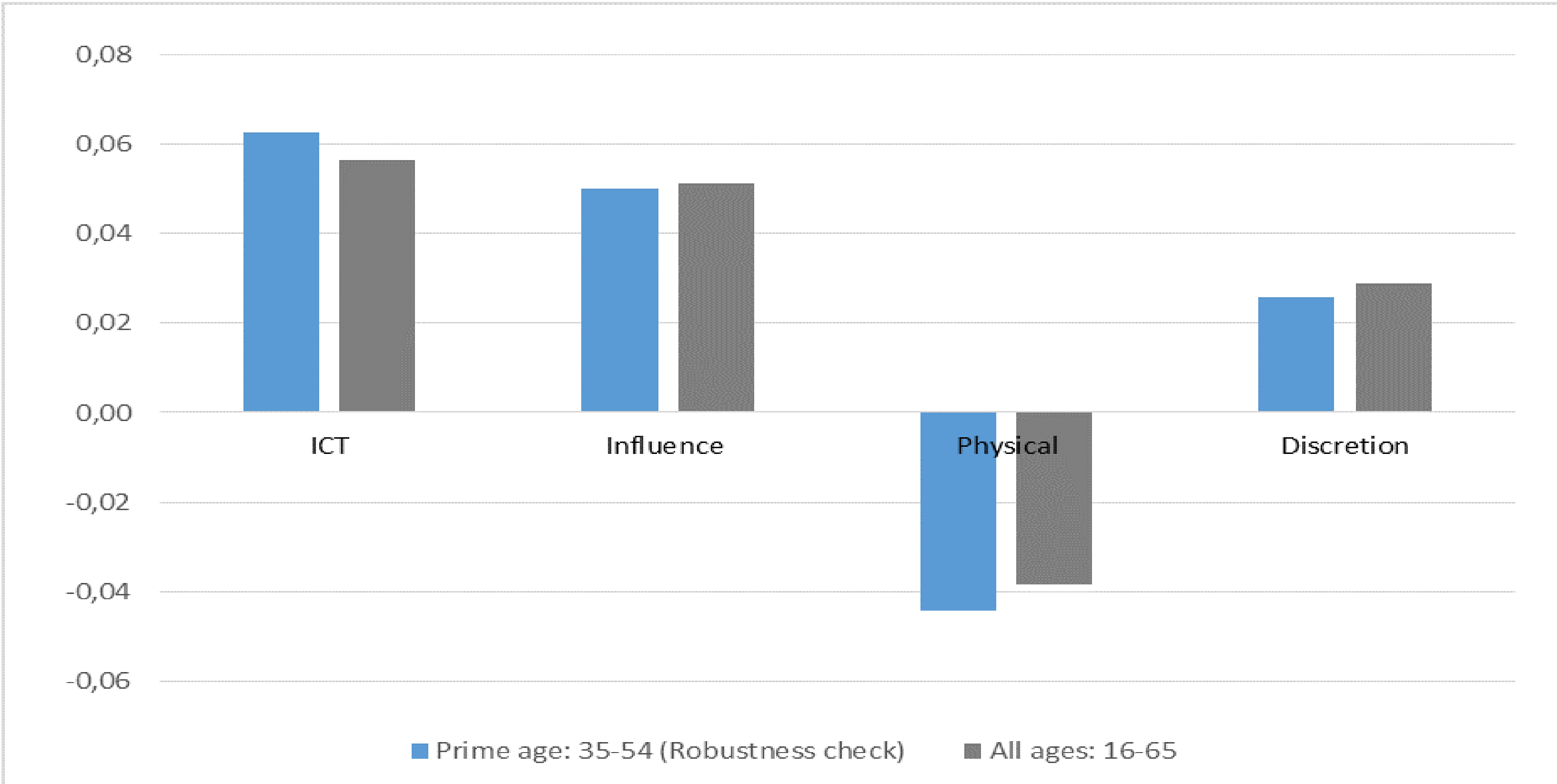
Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six). Sample: employees aged 16-65. Returns to numeracy are statistically significant at 1 percent level. In "task-based approach", returns to numeracy in Greece are statistically significant at 5 percent and 10 percent level in Lithuania, respectively. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-3 ("Baseline approach") and Table A-10 ("Task-based approach"). Country acronyms can be found in Table A-14.
Source: Author's calculations & PIAAC.

Figure A-10: Returns to Numeracy in Task-based Approach



Notes: Coefficient estimates on numeracy scores (standardised to within-country mean of 0 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy, binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six). Sample of "All ages: 16-65": employees aged 16-65. In "All ages: 16-65" case, returns to numeracy are statistically significant at 1 percent level, while returns to numeracy in Greece are statistically significant at 5 percent level and 10 percent level for Lithuania, respectively. Sample of 'Prime age: 35-54 (Robustness check)": full-time employees aged 35-54. In "Prime age: 35-54 (Robustness check)" case, returns to numeracy are statistically significant at 1 percent level with few exceptions. Namely, the return to numeracy in the Czech Republic are statistically significant at 5 percent, whereas the returns to numeracy in Chile, Greece and Lithuania lose their statistical significance (black border bars). Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-10 and Table A-11 (Robustness check). Country acronyms can be found in Table A-14. *Source*: Author's calculations & PIAAC.

Figure A-11: Returns to Tasks; Pooled Sample



Notes: Coefficient estimates on selected job tasks (standardised to within-country mean of 2 and standard deviation of 1) in a regression of log gross hourly wage (in PPP U.S. dollars) on numeracy (standardised to within-country mean of 0 and standard deviation of 1), binary gender indicator and a quadratic polynomial of potential work experience (age minus years of schooling minus six) and the selected job tasks. Sample of "All ages: 16-65": international employees aged 16-65. Sample of 'Prime age: 35-54 (Robustness check)": international full-time employees aged 35-54. Returns to tasks are statistically significant at 1 percent level for both pooled samples. Pooled specification includes country fixed effects and gives same weight to each country. The specific figure replicates estimates in Table A-10 and Table A-11 (Robustness check). *Source*: Author's calculations & PIAAC.