EDUCATION, LABOUR MARKET EXPERIENCE AND COGNITIVE SKILLS: A FIRST APPROXIMATION TO THE PIAAC RESULTS[1]

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ABSTRACT

We study how formal education and experience in the labor market correlate with measures of human capital measured in PIAAC –an international study assessing adults' numerical and reading ability. Three findings are consistent with the notion that, in producing human capital, working experience substitutes formal education at the bottom of the schooling distribution. Firstly, the number of years of working experience correlates with performance in the PIAAC test only among low-schooling individuals. Secondly, holding experience constant, low educated workers who conduct simple tasks on their jobs (calculating percentages or reading emails) perform better in numeracy and literacy tests than similar employees who did not perform those tasks. Thirdly, individual-fixed effect models suggest that workers in jobs intensive in numeric tasks –relative to reading tasks- perform relatively better in the numeracy section of the PIAAC test –compared to the literacy part. The results are driven by workers with basic schooling and hold mainly for simple tasks, suggesting that the previous findings are not generated by sorting of workers across jobs. Overall, our results suggest that the contribution of on-the-job learning to skill formation is about a third of that of compulsory schooling in most of the countries assessed in PIAAC.

JEL Classification: D24, J24

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1. Introduction

Human capital plays a crucial role in shaping labor market outcomes, defined as the cognitive skills that can be acquired in the formal education system or, alternatively by learning on-the-job either by performing certain tasks at work or by occupational training[3]. Since the seminal study of Mincer (1974) the role of both forms of human capital has been measured using earnings equations that relate the individuals' labor market outcomes to the level of education and work experience. However, it is also well known that earnings at a point in time reflect not only the market value of human capital, but also institutional factors, such as collective bargaining, minimum wages or other factors affecting the reservation wages. Furthermore, wages are observed for employees only, making it difficult to infer the contribution of formal education and on-the-job learning on the human capital acquired by large groups of the population. This is unfortunate, because the effectiveness of active labor market policies focused on job training depends on the relative impact of formal education and work experience in increasing human capital.

The empirical literature has addressed those issues by isolating the causal impact of education and work experience through the use of advanced econometric techniques (instrumental variables, natural experiments, etc.)[4]. The results from that literature generally confirm that education and work experience increase cognitive skills and labor market outcomes beyond their relationship with other unobserved individual characteristics (Card, 1994, Angrist and Krueger, 1991, Carneiro, Heckman and Vytlacil, 2010).

Our study draws on new data to estimate the contribution of on-the-job training on several measures of cognitive ability of representative samples of the population of eight European countries, paying special attention to individuals with low education levels.[5] By using measures of cognitive abilities available for representative samples of the population we can abstract from several of the econometric issues that arise because wages or labor market outcomes are available for selected samples of the population or affected by institutional factors.

Our first measure of on-the-job learning is the number of years of work experience. Work experience may vary across similar individuals due to extended periods of unemployment or non-participation in the labor market which, in turn, may affect cognitive skills[6]. On the other hand, an active worker engaged in numeric or literacy tasks may also learn skills through learning on-the-job or training activities[7].

[3] See Rosen (1972).
[4] For an overview, see Card (1999).
[5] We assume that there are no differences between unemployed workers who attend training courses and other unemployed or inactive workers. So, when we compare people of the same age and education with different levels of experience, we will be observing the difference in cognitive skills that have been used for more or less time (considering all possible alternatives - informal work, leisure and occupational, vocational or informal studies - equivalent to each other).
[6] The depreciation of human capital may depend on the duration of non-participation spells and not so much on the level of qualification prior to the period of unemployment. See Jacobson et al. (1993) and Schmieder et al. (2012).
[7] See Becker (1964) and Ben Porath (1967).

The second measure of on-the-job learning takes advantage of the richness of the PIAAC survey, that collects information on a wide array of tasks performed on-the-job (for employed workers) or on the previous job (for unemployed ones). Given that jobs differ in their task content, we analyze whether given the same number of years worked, different intensities in the numeric or literacy tasks (basic or advanced) performed in the last or current job contribute to better numeracy or literacy scores.

However, the capacity of work experience to increase the cognitive skills of a person depends on unobserved factors like, pre-labor market cognitive or even non-cognitive skills[8]. Our analysis takes into account a significant number of factors that approximate individual differences in these dimensions, although since we are unable to control for all the unobserved differences results in the second section are not going to be able to establish any type of causal relationship. For that reason, we implement an individual fixed-effect strategy that draws on the availability of multiple measures of cognitive skills. There are many non-cognitive abilities unobserved by the econometrician and may spur the results. We relate the relative intensity of numeracy versus literacy tasks in her job to the relative score in numerical versus literacy tests.

The abovementioned tests control for a fixed-effect that is common across all cognitive measures, but not for pre-labor market preference for numeracy versus literacy tasks that lead workers to select into jobs with a higher numeracy content. To address that selection issue we assume that very basic tasks like using a calculator or reading emails are unlikely to increase the cognitive skills of workers with high levels of schooling. As a result, any differential performance in numeracy tests associated to those basic tasks among college or high-school workers must merely reflect sorting across jobs, allowing us to purge our estimates from selection effects.

Our results can be summarized as follows. In all eight countries considered (Spain, Italy, Great Britain, Ireland, Norway, Sweden, Estonia and the Netherlands) a higher number of years of experience increase performance in numeracy tests mainly of the least schooled workers and at the early stages of the working career. Secondly, in basically all countries, conducting simple numeracy (literacy) tasks at the job increases the scores in numeracy (literacy) tests mainly among least schooled workers. Finally, pooling data from all countries, we find that workers with basic schooling and working in jobs with a relatively higher intensity in basic numeracy tasks perform relatively better in numeracy tests than in literacy tests. All those results are much weaker among individuals with a high school or a college degree. We argue that those results are consistent with the notion that on-the-job learning through basic tasks is a substitute for formal education for low schooling workers.

The rest of the paper is organized as follows. Section 2 describes the test. Section 3 describes the data. Section 4 discusses the link between working experience and numeracy scores, while

[8] By cognitive skills we mean an accumulation of factors among which stand out the perseverance to achieve a goal, ability of motivation to perform new tasks, self-esteem, self-control, patience, attitude towards risk and preference for leisure - see Cunha and Heckman (2007).

Sections 5 and 6 discuss and quantify the link between tasks on-the-job and numeracy and literacy scores. Section 7 presents the main conclusions.

2. The test

We assume that human capital C is acquired either through formal education S or by learning tasks on-the-job –measured by J. Individuals may also vary in their initial endowment of human capital C_0 –a measure that summarizes the skills acquired prior to entering the labor market.

$$C = \alpha_0 + \alpha_1 S + \alpha_2 J + \alpha_3 J * S + C_0 + \varepsilon$$

The tasks performed on-the-job and formal schooling S may affect the stock of acquired skills C in a non-linear fashion. On one hand, the tasks learnt on-the-job could complement formal education if highly skilled individuals learned the most from performing sophisticated tasks on their job –in which case α_3 would be positive. Alternatively, one could think that on-the-job learning is a substitute for formal education if a certain set of skills –like using a calculator- can be either learnt at school or by practice on-the-job. In that case, α_3 could be negative.

In practice, we cannot observe the exact value of C but can observe different measures, like numeracy or literacy scores in standardized tests. That means that we observe

$$C_m = \alpha_{0,m} + \alpha_{1,m} S + \alpha_{2,m} J_m + \alpha_{3,m} J_m * S + C_0 + \varepsilon_m \qquad m = n, l \quad (2)$$

In our case, the subscript *m* can take two values, depending on the exact measure of skills we use: literacy (*l*) or numeracy (*n*). In what follows, we use two different measures of learning on-the-job J_m. The first measure is the *number of years worked full time*, an indicator of exposure to on-the-job learning. The second measure of J_m denotes the skill content of the current or last job, and reflects whether or not an individual performs *particular tasks on-the-job* - in our case, can be either numeracy or literacy-related. Finally, ε_m is an individual-specific measure of skills that can be either acquired pre-market or by other factors.

We note that both proxies measure different aspects of on-the-job learning. The number of years of working experience is a stock variable that possibly summarizes heterogeneous experiences, depending on the skill content of current and past jobs. On the other hand, models using the task content of jobs to proxy of J_m focus on flow variables –rather than experience, which reflects the cumulative impact of diverse work experiences. Ideally, we would like to disentangle between the impact of current tasks on the job and the cumulative impact of tasks in previous job –i.e., for the whole history of numeracy or literacy task on the job. However, we deal with a cross section, and that information is not available. Hence, when we use tasks on the job as the main regressor, we control for the number of years of working experience.

The parameter of interest. In this study, we mainly focus on α_2 the impact of tasks on the job on overall measures of skills C. Several reasons lead us to expect that α_2 is varies across individuals. We already mentioned that α_2 may vary across groups with different levels of formal schooling depending on whether on-the-job learning is a complement or a substitute for formal schooling. For that reason, we present estimates of the impact of working experience and of tasks on different schooling groups.

Controlling for unobserved heterogeneity. A problem when estimating model (2) is that we rarely observe repeated measures of human capital, particularly of pre-labor market ability C_0. Most likely, workers with a higher level of pre-market skills (i.e. with levels of C_0above the mean) will work on average on jobs where a higher level of skills are demanded (i.e., where J_m, is also above the mean), because firms are more likely to select and retain workers with a better initial endowment of human capital. As a result, workers with a higher endowment of skills will in turn accumulate more years of working experience. The failure to hold pre-labor market ability C_0 constant is likely to result in an upward bias of OLS estimates of $\alpha_{2,m}$ in Model (2). The bias of $\alpha_{3,m}$ can go in either direction, depending on whether firms screening policies vary with the schooling of the worker.

However, PIAAC includes two measures of human capital C_m, *m=n,l*. Assume that conducting numerical tasks on the job has an impact on numeric ability, and that conducting literacy tasks on the job has a similar impact on reading ability. In that case, one can examine if workers who specialize in jobs with a relatively higher numeracy content –relative to the literacy one- end up with a relatively higher numeracy score –relative to the score in the literacy test. In other words, under the assumptions that $\alpha_{2,n} = \alpha_{2,l}$ and that $\alpha_{3,n} = \alpha_{3,l}$ one can take the difference between human capital related to numeracy and that related to literacy:

$$C_n - C_l = [\alpha_{0,n} - \alpha_{0,l}] + [\alpha_{1,n} - \alpha_{1,l}]S + \alpha_2[J_n - J_l] + \alpha_3[J_n - J_l] * S + \varepsilon_n - \varepsilon_l \quad (3)$$

Model (3) identifies the impact of tasks performed on-the-job on particular forms of human capital comparing individuals who have different degrees of specialization on their jobs. In that Model α_2 is identified by examining if individuals who specialize in numerical tasks – relative to literacy ones- tend to perform relatively better in the numerical test than in the literacy test. The advantage of Model (3) over Model (2) is that it implicitly holds constant an unobserved individual fixed-effect that reflects generic initial human capital acquired before entering the labor market.

Potential sources of biases

1. Linearities vs threshold effects. A first source of concern is that Models (1)-(3) deal with numeracy and literacy scores linearly, while many analysts consider thresholds in scores that signal discontinuous changes in respondents' skill levels. At this stage, we do not do much about this problem for two reasons. The first is that we rely on worker-level fixed effects, which are hard to incorporate into non-linear models. The second reason is that our key assumption that the impact of literacy tasks on literacy scores is similar to the impact of numeric tasks on numeracy scores relies is hard to implement in non-linear settings.

2. Cohort effects/skill mismatch. A prevalent issue in the analysis of the variation of skills lies in distinguishing the role of cohort versus life-cycle effects (Green and Riddell, 2013). Test scores are typically lower among aged individuals, raising a discussion of whether that age gradient reflects improvements in the educational system or a decay in cognitive abilities with age. In our case, cohort effects are collected in the term C_0, which may bias the estimates in models that compare the performance in the test across workers that conduct more numeric or literacy tasks on their jobs –for example, Model (2). However, when we relate relative performance in the numeracy vs the literacy test to the relative intensity of math skills on the job, we implicitly hold constant cohort effects C_0. Thus, the presence of cohort effects does not necessarily bias the estimates of Model (3).

Similar considerations regard the existence of *skill mismatch* (or the presence of highly skilled workers locked in jobs involving basic tasks). In principle, skill mismatch can be considered as a negative correlation between unobserved measures of pre- labor market human capital C_0 or between skills ε_m and the skill content of a job

$$E[(J_m)(\varepsilon_m)] < 0 \qquad or \quad E[(J_m)(C_0)] < 0$$

Indeed, as we discuss in Table 2, a non-negligible fraction of college workers in the countries we consider conduct at most basic numeracy or literacy tasks on their jobs. The fraction ranges from 13% in Estonia to 22% graduates conducting at most basic tasks on the job in Sweden or Italy. It is not clear how mismatch affects our estimates. Firstly, our focus lies on workers with basic schooling, who are unlikely to work on jobs requiring skills below their abilities. In addition, if mismatched workers work in jobs with a similarly poor content of numeracy and reading tasks, once we take differences in numeric vs literacy task intensity in Model (3), we implicitly control for the degree of mismatch.[9] Finally, we note that it is very likely that there is substantial dispersion in the skill content of jobs and in the workers' ability to acquire skills from exposure to those tasks. In other words, α_2 is very likely to be heterogeneous across workers. At this stage, we can only aim to recover the average effect of on-the-job learning on skills, leaving an analysis for heterogeneous impacts to a future version of the study.

3. Comparative advantage. Finally, there is source of correlation between task specialization and the initial comparative advantage of individuals for numeric or literacy tasks that may bias our estimates. Imagine that individuals with a better initial endowment for numerical tasks sort into jobs requiring numeracy-intensive tasks. More formally:

$$E[(J_n - J_l)(\varepsilon_n - \varepsilon_l)] > 0$$

In that case OLS estimates of α_2 would be upwardly biased, as they attribute to on-the-job learning what really is the result of workers sorting across jobs. In other words, even if doing specific tasks on-the-job did not increase skills at all, an OLS estimate of α_2 could be positive

[9] Skill mismatch would be problematic if, for example workers with skill levels above the average end up in jobs involving very low numeric tasks but average literacy content (as in that case the degree of task specialization $[J_n - J_l]$ would measure not only differential performance of numeric vs literacy tasks, but also differences in skill mismatch). We are not aware of evidence about the relationship between skill mismatch and the differential numeric content of job tasks.

simply because individuals with an initial (pre-market) comparative advantage in math end up in more math-intensive jobs.

We control for that second source of bias using further assumptions. Our main interest is on whether or not workers with the lowest levels of schooling acquire (some form of) human capital by performing simple tasks at their jobs –for example, reading a bill or using a calculator. Individuals with a college degree are unlikely to learn much by performing those tasks. Nevertheless, math-inclined college workers are still likely to sort into jobs that require specializing in numeric tasks. That is, we expect that for workers with basic schooling, the OLS estimate of a regression of $C_n - C_l$ on $(J_n - J_l)$ is

$$\hat{a}_{2,basic} = \alpha_2 + \frac{E[(J_n - J_l)(\varepsilon_n - \varepsilon_l)]}{Var(J_n - J_l)}$$

That is, $\hat{a}_{2,basic}$ captures the causal impact of tasks on human capital plus the selection effect due to workers' sorting across jobs. On the contrary, for workers with high school or college, our hypothesis is that $\alpha_2 = 0$, so an OLS regression of $C_n - C_l$ on $(J_n - J_l)$ is

$$\hat{a}_{2,high\ school} = \frac{E[(J_n - J_l)(\varepsilon_n - \varepsilon_l)]}{Var(J_n - J_l)}$$

So $\hat{a}_{2,basic} - \hat{a}_{2,high\ school}$ is a consistent estimate of the parameter α_2. In other words, we run Model (3) on a sample of individuals with basic schooling, and then on a sample of individuals with high school. The difference between both coefficients reflects a causal impact of simple tasks on-the-job on human capital increases that holds constant the selection effect.

We make two final notes. The first one is that we have assumed that $\alpha_2 = 0$ for individuals with high school or college. Obviously, under such assumption, Model (3) cannot establish whether simple tasks increase human capital differentially for individuals with high school or college. Secondly, the assumption of $\alpha_2 = 0$ for individuals with a high school degree is realistic mainly for "simple" tasks. However, the assumption may be strong if the tasks considered are complex ones, as those may help anyone to build human capital. Hence, when estimating Model (3) we control for the presence of advanced tasks on-the-job.

Testable hypotheses

In sum, we test three main hypotheses:

- Does performance in numerical tests increase with job market experience differentially among workers with basic schooling than among workers with high school or college? We test that hypothesis by estimating $\alpha_{2,m}$ and $\alpha_{3,m}$in Model 2 using experience as a measure of *J*.

- Holding experience constant, is the performance in numerical (literacy) tests higher among workers who conduct simple tasks on their jobs? We test that hypothesis by estimating $\alpha_{2,m}$ and $\alpha_{3,m}$in Model 2 using performance of numerical and literacy tasks as measures of J_m

- Does performance in numerical tests –relative to literacy tests- increase with differential exposure to simple math tasks –relative to simple literacy ones ? We test that hypothesis by estimating α_2 and α_3 in Model (3)

3. Database

Our data source is the *Programme for the International Assessment of Adult Competencies* (PIAAC), provided by the OECD and collected between August 2011 and March 2012. PIAAC includes an international comparable database about skills and tasks developed by adults in the workplace for 24 countries. For data related reasons. we mainly use eight of them: Spain, Ireland, Italy, Great Britain, Netherlands, Estonia, Sweden and Norway. Those are the countries with the largest samples and with detailed information about the number of years of working experience and age. However, we have also used Korea, Czech Republic, France, Finland, Russia and Slovak Republic in some regressions.

The survey tested a representative sample of individuals in each country to construct standardized measures of their numeric and literacy cognitive skills. The survey was implemented either by computer or on paper and pencil[10]. The exam includes questions about three different domains: literacy, numeracy and problem solving in technology-rich environments, but we only use the first two, as the latter is not available in all countries[11].

In addition, PIAAC contains internationally comparable information about the educational attainment of individuals and the number of years they have worked as well as detailed information about the tasks performed in the current or last job needed to construct J_n and J_l.

Experience. In particular, work experience is obtained by the individuals' responses to the question: *"In total, approximately how many years have you been in paid work? Include only those years in which you worked for six months or more, full time or part time?"* In this version of the paper, we use only one of the ten different imputations of the score for each test for each individual, so that the results are preliminary. Each score is measured on a 500-point scale and, for this version, we have not standardized the scores.

Tasks. The survey asks each employed respondent about how many times he or she conducted a particular task during the last month. The survey asked non-employed respondents about the tasks done in their last job. The number of tasks listed in the survey is large, and we have classified those in mathematical and literacy-related tasks. We include as mathematical tasks the following: elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams, elaborating graphs or using algebra. We classify as literacy

[10] Individuals who answered with paper exams have been controlled with a dummy in the regressions.
[11] Details about the definition of each domain are given by OECD (2013).

tasks reading email, reading guides, reading manuals, writing emails, writing reports, reading articles, reading academic journals, reading books and writing articles.

Formal education. We group individuals in three schooling levels. The first is primary education or less. The second is composed of individuals having completed either baccalaureate studies or those modules of Professional Training (FP) that, according to the ISCED classification, do not constitute university education. The third group is composed of individuals with any type of university education, including the higher module of Professional Training (FP) in each educational system.

Sample selection. To obtain a large sample of individuals of different countries we pool employed and unemployed individuals as well as females and males. However, in several instances, we restrict the sample to respondents below 45 years of age as the link between experience and skills weakens considerably after that age. In addition, as we compare in many instances the relationship between experience on-the-job or tasks and performance at the tests across schooling groups, we cut the sample below 26 to avoid measuring experience at years when college graduates are unlikely to work. The 25-year age limit also avoids the problems associated with greater practice in exam preparation among college students. However, in some instances, we have analyzed samples of 16-45 and 16-65 year old workers. The main sample thus selected contains 19,738 individuals between 25 and 45 years of age from the eight countries mentioned above.

Summary statistics: experience and tasks

Table 1 shows summary statistics for the baseline sample of prime-aged individuals (aged 25-45). The performance in the numeracy and literacy tests varies across countries and schooling groups in ways that have been discussed in a number of studies. The fraction of prime workers with basic schooling is 19% in the full sample, being highest in Spain (41%) and lowest in Sweden (7.8%). The average number of years worked does not change much across countries, in contrast.

Table 2 shows to what extent workers use different tasks on their job. As discussed in Section 2, we distinguish between simple and advanced tasks, as their impact on human capital accumulation are likely to vary across educational groups. Regarding numerical tasks, we used principal component analysis to classify tasks into advanced and simple, and identified elaborating a budget, using a calculator, reading bills, using fractions or percentages and reading diagrams as simple tasks. Conversely, we classify elaborating graphs or using algebra as advanced tasks[12]. Similarly, we classified reading email, reading guides, reading manuals, writing emails, writing reports and reading articles as simple literacy tasks, while reading academic journals, reading books and writing articles were classified as advanced literacy tasks.

[12] Principal Component Analysis helps us in identifying to what extent those tasks vary jointly across jobs. Two main factors account for about 70% of the total variance. The first factor put equal weights on all tasks, while the second factor weighted only the last two (elaborating diagrams and using algebra). Those results led us into classifying elaborating diagrams and using algebra as advanced tasks, while we consider the rest as basic tasks.

Table 2 shows the fraction of individuals who report having performed in their current or last job one of the basic or advanced tasks, by schooling group. We note three findings in Table 2. As expected, the fraction of individuals who report having performed a basic task is larger among those with basic schooling than among those with college. Secondly, the fraction of respondents having performed advanced tasks increases again with schooling in all the economies. Finally, around one third of individuals with basic schooling perform at least one of the simplest tasks. The fraction is remarkably similar across all countries, despite the wide variation in the fraction of individuals with basic schooling or in the industrial composition. The variation in the fraction of respondents with college degree who report having performed advanced tasks is much higher. More than 70% of Nordic European graduates conduct at least one advanced task in their job (that is, in Norway, Sweden, Netherlands or Estonia) while the comparable fraction is around 60% in Spain, Ireland or Italy. The most common basic tasks performed most frequently are using of fractions, a calculator, and elaborating budgets. Conversely, among individuals with high educational levels, the most common advanced tasks are preparing graphs and reading books and academic journals.

Thus, the statistics in Table 2 suggest that, in each of the countries we consider, a nontrivial share of individuals with basic schooling perform simple tasks at their jobs –having at least the possibility of using and acquiring some skills.

The importance of cognitive skills

Before going on to investigate why labor market experience might positively impact cognitive skills, it is worth analyzing the degree of association between declared wages and cognitive skills, as measured by the tests in the PIAAC sample. Only to the extent that both variables are correlated some conclusions about the importance of cognitive skills for job performance can de drawn. Figure 1 relates the results of numeracy and literacy tests to wage earnings in each decile of the distribution of the numerical score in Spain. The statistical association is particularly pronounced at the higher deciles of the wage distribution, suggesting that cognitive skills measured by the tests are relevant to job performance in all deciles of the distribution –see Hanushek et al, 2013 for similar evidence. The finding of a strong correlation between performance in PIAAC and wages at the top of the wage distribution is consistent with the idea that cognitive skills are rewarded in the labor market, especially at the top of the wage distribution.

A positive relationship between wages and cognitive skills lead us to think that cognitive test scores are a good approximation of the individual human capital stock. Having access to cognitive tests is convenient for researchers since most of the empirical work usually use direct wages as a proxy of human capital despite their important empirical limitations. In particular, in contrast to test scores, wages are only observed for employees whose reservation wage might be completely heterogeneous, wages might cyclically vary depending on the demand for particular skills. Furthermore, labor market institutions such as minimum wage and collective bargaining agreements also affect wages, raising issues when one tries to elicit human capital of workers from the distribution of wages.

4. Work experience and cognitive skills

Table 3 tests Model (2) by running country-specific regressions of the numeracy score in PISA on a flexible function of years of working experience, interacted with schooling dummies. However, to attain more precision, we only interact with schooling the main effect of experience, assuming that the squared term in experience is common across schooling groups (a strong assumption we relax below). In addition to years of experience and education, we also include demographic and attitudinal variables as controls[13]. To allow the effect of experience on test scores to vary over the life span, experience is included as a second-order polynomial (Table 3).

Regardless the country of residence and among respondents with basic schooling, ten years of labor market experience are associated with an increase in the score in the numeracy test. For example, a Spanish worker with basic schooling and 15 years of experience scores 8.5 (=.85*10) additional points in the numeracy test than a similarly schooled worker with 5 years of working experience. The same increase of 10 years results in an increase of 20 points in the numeracy score in Norway (the standard deviation of the marginal distribution of the scores is about 50 points). While cross-country estimates are hard to compare because of the variation in the standard deviation of the scores across countries, the finding that experience increases the numeracy score of respondents with basic schooling holds in all countries considered.

Conversely, for university graduates in all countries considered, the correlation between years of working experience and performance in the numeracy test is rather weak. Note that the interaction between years of experience (actually, its deviation from 15) and the dummy for college graduate is negative and statistically different from zero at the 95% confidence level in all countries considered –see row 3 of Table 3. One extra year of experience correlates much less strongly with numerical scores among college graduates than among respondents with basic schooling. For example, a Swedish college graduate with 15 years of experience in the labor market has a numeracy score that is only 1 point higher than a similar college graduate with 5 years of experience (=10*(1.384-1.28)). For a respondent with basic schooling, ten extra years of experience increase numeracy scores in PIAAC by 13.8 points, an estimate that is about an order of magnitude larger than respondents with a college degree. The impact of labor market experience on the numeracy score of college graduates are somewhat larger in Great Britain than in Sweden. A British college graduate with 15 years of experience has about 4 points higher score than a similar graduate with 5 years experience =(10*(1.147-.676)). Again, the estimated impact is modest compared to the return of 11 points of extra ten years of experience for a British student with basic schooling.

Figure 2 illustrates graphically the different profiles for all countries. The skill returns to one extra year of experience at job entry are very high for low educated individuals -and fade out as time passes. However, numeracy skills correlate much more weakly with experience among college graduates.

[13] In particular, we include a dummy for foreign-born, another for married, dummies for state of health and attitudes towards learning and four dummies of age in 5-year bands.

Table 3B relaxes the strong functional form assumptions implicit in Table 3. There, we conduct local linear regressions of the numeracy score on the number of years of experience separately for each education-country cell. The advantage of that specification is that we can capture more accurately the concavity of the effect of experience on numerical test scores while at the same time we hold the covariates in footnote 14 constant[14]. The flexibility of the models estimated in Table 3B comes at the cost that some cells have too few observations to conduct the analysis (cases of Netherlands and Sweden). The results in Tables 3B and 3 are qualitatively similar: in all countries but in Estonia the link between experience and the numeracy score is strongest for individuals with basic schooling during the first year of working experience. The effect of one extra year of experience is still noticeable after 15 years in four out of the six countries where we could estimate the regression (the exceptions being Italy and Estonia). As the findings in Table 3 suggest, the link between years of working experience and average numeracy scores among respondents with a high school degree or with college is at best weak.

Summarizing, the evidence shown in Tables 3 and 3B is consistent with the notion that formal education and labor market experience are substitutes in the accumulation of cognitive skills. Given that in both models average numeracy scores are 30 points higher among respondents with university degrees than among those with primary education (not shown), the contribution of labor market experience to explaining the variance of the numeracy tests results is three times lower than the effect of education in Spain (.28=8/30). However, in Norway, the contribution of the number of years of working experience is about two thirds that of schooling in Norway (.66=19/30).

Several reasons can account for the weak impact of years of working experience on numeracy scores among college graduates. One of them is the incidence of skill mismatch among college graduates, mentioned above. A fraction of skilled college workers can be locked up in jobs requiring very few skills, and more years of exposure to on-the-job learning may not boost numeracy scores much. Alternatively, one can think that there are “ceiling” effects, and that already skilled workers may already start their working life up in the distribution of scores. While plausible, we doubt that those considerations can be the whole story, as further years of working experience increases numeracy scores more among workers with basic schooling than among college graduates holds in basically all countries, while the degree of skill mismatch should vary. Secondly, as already mentioned wages and numeracy scores correlate strongly at the top of the wage distribution, indicating that “ceiling effects” may not be that strong.

The following sections examine the channels that explain why labor market experience might increase the test score of low educated individuals.

[14] Namely, we pose a flexible relationship between numeracy scores and experience, while controlling for a linear index of the covariates in Footnote 14. We then fit local linear regressions of numeracy scores and each of the covariates in the index on experience and take the residuals from those regressions. We make a linear regression of those residuals to partial out the impact of the linear index of covariates. Finally, we fit local linear regressions of numeracy score minus the estimated local index on experience. See Robinson (1988).

5. Job tasks and cognitive skills

We now test our second hypothesis: simple tasks correlate with numeracy and literacy scores for workers with basic schooling. We regress the numeracy and literacy test scores on indicators of the type of tasks performed on-the-job, all interacted with dummies of school attainment. In particular, the indicator "basic numeric tasks" ("advanced numeric tasks") takes value 1 if the worker reports having performed *any* of the basic numeric (advanced) tasks listed in the data section during the last month, and zero otherwise. As in previous specifications, the country-specific regressions shown in Table 4 hold constant the number of years of experience and the socio-economic factors described in Footnote 14.

Among individuals with basic education, those who perform basic math tasks at their work - using a calculator, calculating fractions or percentages– score between 3.2 and 19 points more in the numeracy test than those who do not perform such tasks -even within the same age cohort and the same work experience. The impact of basic tasks on numeracy scores are larger than the average in Sweden and Ireland, and below the mean in Spain, Italy or Estonia –the latter estimate being not statistically different from zero. Similarly, within the set of individuals with basic education, keeping the number of years of working experience and age constant, those who conduct advanced tasks in their jobs –such as preparing graphs, doing simple or complex algebra or using regression analysis – obtain between 7 and 30 extra points on the numeracy test. The estimates of the impact of conducting advanced tasks on the job on numeracy scores are larger in Sweden or the Netherlands –where advanced task increase the score by at least 20 points- than in Great Britain or Spain –where the estimates are about 6-8 points. However, the link between advanced numerical tasks and numeracy skills is generally less precise than that between simple tasks and numeracy skills.

Secondly, Table 4 suggests that the link between conducting simple numeracy tasks on-the-job and numeracy scores varies across schooling groups, being weakest among respondents with either a high school or college degree. The interaction between "simple numerical tasks" and either "bachelor" or "college" dummies is negative in all countries, although it is not very precisely estimated. A possible explanation for the weak impact of conducting simple numeracy tasks on numeracy scores among college students is the presence of negative sorting into jobs: individuals with high education levels who end up performing simple tasks must have a low stock of pre-market skills to start with. Another interpretation is that performing basic tasks enhances the acquisition of skills among workers with low levels of formal schooling, but not among workers that acquired those skills in the formal education system.

Finally, and despite the imprecision of the estimates, the results in the 6th row of Table 4 suggests that, in 6 of the 8 countries considered, workers with college degree have high numeracy returns to performing advanced numeric tasks on their jobs. For example, a Spanish college graduate performing advanced tasks in his or her job scores 15.7 points (=7.18+8.5) higher in the numeracy test than a similar college graduate who does not perform those tasks. The results are similar among Italian, British or Irish college graduates, who obtain numeracy skill returns of performing advanced numerical tasks of 20 points (=8.1+12.2), 14 points (=6.9+7.4) or 18 points (8.3+10.3) respectively. However, the latter estimates are imprecise.

Table 4B conducts a similar exercise by regressing literacy test scores on indicators of the literacy tasks performed on-the-job. The results are remarkably similar to those we have just described, and we do not comment them in detail.

Overall, the results using specific tasks are again consistent with the hypothesis of substitution between simple tasks and formal schooling at the bottom of the schooling distribution. Namely, the findings in Table 4 suggest that conducting basic numeric (literacy) tasks on-the-job increases the numeracy (literacy) skills of workers with little formal schooling, but there are no skill returns to tasks on-the-job among workers with a high school or college degree – who could have learnt those skills already in the formal schooling system. On the other hand, there are numeracy skill returns to conducting *advanced* numerical tasks among all workers, regardless of their schooling level, and we cannot rule out the hypothesis that college graduates benefit the most from performing those tasks. In that sense, it is tempting to conclude that learning and conducting basic numerical tasks on-the-job can be a substitute for formal schooling, while conducting advanced tasks complement formal schooling investments. However, one must be cautious. We cannot rule out an alternative explanation based on the heterogeneity of initial endowments. Namely, sorting between workers and jobs leads the least schooled workers with a better initial endowment of human capital to end up working in jobs that involve conducting and learning basic tasks – the best jobs available for that group. The same sorting process results in more schooled workers with a worse initial endowment ending up in jobs that *only* involve basic tasks –the worse jobs available for the better schooled.

In the next Section we implement a test of Model (3) that partially controls for the quality of an initial endowment of human capital.

6. Identifying a causal relationship

In Section 3 we argue that the estimates in Tables 3 and 4 may be affected by omitted variable biases, as the unobserved initial endowment of human capital is likely to be correlated with years of working experience, the complexity of tasks conducted on the job and performance in numeracy tests. We also argue there that regressing the relative performance in numeracy vs literacy tasks on the relative specialization in numeracy tasks on the job implicitly controls for the initial endowment of human capital.

This simple idea relied on two assumptions. The first is that the numeracy and the literacy skills of individuals are not perfectly correlated and do not result from a common individual-specific factor, as in that case there would not be meaningful variation in scores to start with. The second assumption is that jobs vary in their intensity of numeracy versus literacy task. We provide now evidence that supports the notion that different jobs involve different bundles of numeracy and literacy tasks, paying special attention to those available for the least skilled.

We note that to implement Model (3) empirically, we need wide variation in $task_{num} > task_{lit}$ across jobs. Hence, we build a measure of task intensity that departs from that used in Table 4. For each person, we construct a measure of task intensity by computing the number of numeric tasks performed in the job. If a worker reports performing *all* basic numeric tasks on her job (i.e. if she elaborates a budget, reads a diagram, uses a calculator *and* computes a fraction at least once a month in her current or last job) we grant her 1(=4/4) in "Basic Math tasks". If she conducts only one of the four tasks, we grant her .25 =(1/4). 15% of basic schooling workers are granted 1. That way of counting intensity seems appropriate since, as we mention in Footnote 12, a principal component analysis of types of numeric tasks one factor with equal weights accounts for most of the variance.

We define "Basic literacy tasks" in a similar fashion. The degree of specialization is defined as the difference between "Basic math task" and "Basic literacy task".

An illustration: Task specialization by occupation and industry

We illustrate the different degrees of numeracy specialization by aggregating skills at the occupation and industry level. Table A2 of the Appendix shows the different task intensity of industries of basic schooling individuals and Table A3 of the Appendix shows the different tasks intensity of occupations of the same sample. We focus on occupations (Table A3). Numeracy and literacy tasks have been summarized separately by Principal Component Analysis and the first component has been normalized to the interval (0,1) in order to provide a ranking of the task content of the occupation. Examples of the main tasks conducted on-the-job are also provided in Tables A2 and A3 –note that all tasks are normalized by the task-specific mean, so a number above one implies that workers in the occupation conduct the particular task more often than the average.

To fix ideas, we examine two polar cases. The first are *personal care workers* (occupation number 53), who constitute 9.8 % of all individuals with basic schooling in the full sample. Workers in that occupation rank relatively high in literacy tasks (0.20) but less so in the numerical task ranking (.05, Table 7, second column). The tasks conducted by the average person in the occupation give clues about the rationale for those rankings. Personal care workers elaborate budgets, read diagrams or use calculators with an intensity that falls well below the mean (i.e., the corresponding entry under each of those tasks is well below 1). Conversely, personal care workers read guides or emails more frequently than the average worker does. In that sense, personal care workers are specialized in literacy tasks.

The opposite extreme of the spectrum are *street vendors* or *sales persons* (occupation number 95) an occupation that employs 6% of all individuals with basic schooling in the full sample. Those workers rank much higher in the numeracy scale (.20) than in the literacy scale (.03). The reason is that street vendors do not perform *any* literacy task whatsoever in their jobs (the entries below "read email" or "read guides" are all zero). However, and despite the fact they do not perform many numerical tasks, but do have to use fractions and percentages.

Note that both occupations do employ workers with very different **levels** of numeracy or literacy skills –street vendors may well score worse in both numeracy and literacy scores than personal workers. However, the relative specialization in tasks is very different and our test only examines if both groups score **relatively** better in the numeracy test.

Figure 3B provides a visual test of the variation that identifies the parameter of interest α. We compute the relative task specialization and the difference in test scores, both at the 2-digit occupation level and plot one against the other. The relationship is positive: workers in occupations with math oriented tasks perform relatively better in the numeracy test.

Grouping tasks and skills at the industry level provides a similar picture. Workers with basic schooling in agriculture, mining and quarrying, manufacturing, water supply, administrative and support services, other services and activities of households as employers do not do much in either math or literacy. However, individuals with basic schooling who work in construction, wholesale and retail trade or in financial and insurance activities are specialized in numeric tasks. Finally, respondents in public administration, education, human health or professional, scientific and technical activities are relatively specialized in literacy-related tasks –relative to numeracy ones.

Regression analysis

Table 5 implements a version of Model (3) on the full sample of countries.[15] We pool observation of all countries and introduce country-specific dummies. The numeracy and literacy scores are normalized by the country-specific standard deviation. The first set of regressions use the full sample of workers (between 16 and 65 years of age) and do not distinguish between simple and advanced tasks.

The coefficient of $task_{num} - task_{lit}$ in the first row, fourth column of Table 5 is .22, implying that, relative to workers whose jobs have a similar incidence of numeric and literacy tasks, workers with basic schooling specializing fully in numerical tasks perform 23% of one standard deviation better in the numeracy test than in the literacy test. Interestingly, the impact of full specialization in numeric tasks among workers with high school is only about 10.5%=(.22-.105) of one standard deviation -half that estimated for workers with basic schooling. The impact of full specialized in numeric tasks workers with a college degree is 17% (=.22-.0547) of one standard deviation, again lower than that among workers with basic school. The results are virtually unchanged when we introduce occupation and industry dummies (columns 4-6 in Table 5) or when we expand the sample to countries with lower sample size (columns 4-6 in Table 5B).

Overall, the results in Table 5 are again consistent with the notion that practicing tasks on the job increases skills of workers, and that such effect is strongest for workers with basic schooling. The result points again at formal schooling and practice on the job being

[15] We pool all countries for this analysis to achieve more precision. While the return to different tasks varies across countries to some extent, the results in Tables 3 and 4 support the notion that the broad returns to tasks and experience are qualitatively similar across countries.

substitutes –a perhaps surprising finding, as one could well expect that the performance of tasks on the job reinforces pre-labor market differences associated to differences in formal schooling.

Heterogeneity by age groups. As mentioned above, there may be substantial heterogeneity in the link between tasks conducted on the job and the acquisition of human capital. Green and Riddell (2013) document a cohort-level fall in literacy after age 45, suggesting that skills deteriorate over the life-cycle. Hence, we split the sample below and above 45 years of age. Remarkably, the estimated link between specialization in numeracy tasks and human capital is very similar in the full sample and in the below-45 sample: full specialization in numeracy tasks increases the relative numeracy score by 22% of one standard deviation in the full 16-65 sample and by 23% of one standard deviation in the 25-45 sample. The only noticeable difference across specifications is that the impact of full specialization in numeracy tasks on relative numeracy scores is slightly lower in the prime age sample of college graduates: 17% (=.225-.0547) of one standard deviation in the full sample vs 15%=(.229-.0784) of one standard deviation in the prime age sample.

Those results suggest that possible skill deterioration over the life cycle is compatible with a positive link between tasks conducted on the job and relative performance in numeracy vs literacy scores. The observed decline in literacy among older workers could be explained by differences in the type of tasks conducted in job over the life cycle, an area we plan to examine in closer detail.

The role of sorting across jobs. A second source of concern is that the estimates in Table 5 reflect workers' sorting across jobs according to their initial endowment of skills. Section 3 discusses that the extent of sorting can be inferred by examining the differential impact of simple vs advanced tasks on relative performance across workers with different schooling levels. The idea is that conducting simple tasks on-the-job cannot contribute much to college workers' human capital, so any impact of those tasks on numeracy vs literacy scores must reflect sorting across jobs –or reverse causality that runs from initial human capital to tasks.

The estimates in the first row, first column of Table 6 implies that workers with basic schooling who fully specialize in numeracy tasks on their jobs obtain 12 percent of one standard deviation in their numeracy test –compared to workers who are equally specialized in numeric and literacy tasks. In column 2 we introduce dummies for each occupation (at the two-digit level), thus using variation in tasks within the same occupation group. Finally, column 3 adds industry dummies. The results do not change substantially and are always statistically different from zero at the 95 percent confidence level. Columns 4-6 focus on the sample of workers in prime age, suggesting similar results. Finally, Table 6B expands the sample by introducing 6 more countries (Czech Republic, Russia, Korea, Slovak Republic, France and Finland). The estimates are slightly smaller, but very similar given sampling error.

The estimates in the second row of Table 6 contain the interaction between "Specialization in basic numeracy tasks" and high school degree, which are all negative, precisely estimated, and their absolute magnitude is about 70% the size of those in the first row. For example, focusing on the first column and first and second rows of Table 6, we notice that, for workers with a high school degree, specialization in basic numeracy tasks results only in 4.34 percent of one standard deviation (=11.8-7.46) higher score in the numeracy test. The effect of full specialization on relative numeric scores is almost a third of the one estimated for the basic school group (11.8 percent of one standard deviation). The results for individuals with a college degree are about 6.5 percent of one standard deviation =(11.8-.0535). The estimates in the third row of Table 6, containing the interaction between specialization in basic numeracy tasks and a college degree are not statistically different from zero, but their magnitudes are very close to those of the high school group.

Overall, we draw three conclusions from Table 6:

1. Basic school respondents who fully specialize in simple numeracy tasks obtain higher numeracy scores compared to those who do not specialize. The magnitude of the impact is about 12% of one standard deviation, and is present in basically all samples.

2. Respondents with a high school or a college degree who fully specialize in simple numerical tasks also obtain higher scores, but the difference is much smaller, between 4 and 5 percent of one standard deviation. Under our assumptions that simple tasks cannot add much to the skills of workers with some degree of formal education, the 4-5 percent effect reflects mainly sorting of math oriented workers into math intensive jobs.

3. Those patterns are not present for the specialization in advanced numeric tasks, whose impact on relative numeric scores is, if anything, increasing in formal schooling.

Those conclusions are consistent with the idea that simple tasks on-the job is a substitute for formal schooling at the bottom of the schooling distribution.

Adjusting estimates for sorting across jobs. The finding that specialization in basic numeracy tasks results in a weaker relative performance in the numeracy test among workers with either a high school or a college degree than within the group of respondents with basic schooling is consistent with our conjecture in Section 2. There, we argue that workers with a high school or college degree cannot increase their numeracy skills by performing simple tasks on-the-job, as those skills can be acquired in the formal school system. Hence, the 4.34 percent of one standard deviation differential increase in the numeracy score when a worker with a high school specializes in basic numeracy tasks degree mainly picks up a selection effect.[16] Subtracting the sorting effect (4.34) from the 11.8 estimate in the first column yields 7.4% of one standard deviation as the impact of full specialization on numeracy scores, once one takes into account selection effects.

[16] Some evidence in support of the notion that specialization in simple numeracy tasks cannot boost the relative performance in the numeracy test among workers with a college degree is found in rows 4-6 of Table 5. There we show the impact of specializing in "advanced numeracy tasks", which results in similar, if not higher, relative performance in the numeracy test. Arguably, specializing in advanced tasks like running regressions or using advanced algebra contributes to boost the numeracy skills of workers with a college degree (as opposed to specializing in using a calculator) suggesting that the estimates in rows 5-6 do pick up both on-the-job learning and selection effects.

Assessing the magnitude of the estimates

Overall, the results are consistent with the hypothesis that on-the-job learning may substitute formal schooling for workers with basic schooling. However, that is a qualitative assessment. We conduct now some back of the envelope calculations to assess how large is the response of skills to exposure to on-the-job learning relative to the response to exposure to formal education.

The estimates in Table 6 suggest that specializing in numeracy tasks increases the differential numerical score of individuals with basic education by about 7 points. The standard deviation of the score is 50 points, so specialization in basic numeracy tasks increases numeracy skills by 14% of one standard deviation. If we further assume that there are selection effects that can be identified by the impact of specialization on numeracy scores among high school graduates, the corresponding estimate would be 4 points. Those 4 points are obtained as the 7 points return of basic school workers - first row first column of Table 5- and the 3 points return of high school workers –obtained by adding up the first and second rows of Table 5, column 1. Using again the 50 points standard deviation, the impact of specialization in basic numeracy tasks on relative performance in numeracy tests would then be 8% of one standard deviation (=4/50). As we lack information about complete data on tasks performed on all jobs during the working history of a worker, we cannot establish if those 8%-14% responses are obtained in one year of experience or more. Hence, we make the rather conservative assumption that they are acquired along 12 years of experience (the sample average, shown in Table 1). So one year of experience increases numeracy skills by between 0.67% and 1.2% of one standard deviation.

Hanushek et al. (2015) estimate that increasing one year of compulsory education increases skills by between 2.7% and 2.9% of one standard deviation in the United States. Hence, one extra year of schooling would be equivalent to between 2.5=(2.7/1.2) and 4.3 years (=2.9/.67) of on-the-job learning.

7. Conclusions

Numeracy skills account for a substantial share of the variation in labor market outcomes. This paper studies how on-the-job learning contributes to the acquisition of numeracy and literacy skills in eight countries that implemented the PIAAC survey, focusing in individuals with basic schooling. The results, which are preliminary and therefore require further analysis, suggest that in all countries considered labor market experience is associated with an increase in cognitive skills at the beginning of the working life and specially in the case of workers with low educational levels.

To provide some evidence for the channels behind this evidence, we examine if the type of tasks performed at work explain the effect of labor market experience on the accumulation of cognitive skills. The first results show that, indeed, the type of tasks performed at work matter. Within the group with primary education, the scores in numeracy tests are between 5 and 15 points higher among individuals who perform basic numeracy tasks at work –such as using a calculator, calculating percentage or reading graphs. These basic numeracy tasks contribute little to the scores in numeracy or literacy tests of respondents with a high school or college degree. By contrast, the results in the tests are higher among the group of qualified individuals who perform advanced tasks. Those results remain robust even under controlling for a worker's fixed effect by analyzing how the relative performance in numerical versus literacy test scores varies with the differential exposure to numeracy versus literacy tasks on-the-job. Our results are consistent with the notion that formal schooling and on-the-job training are substitute inputs in human capital production for workers with low schooling levels.

We still view our results as preliminary. If confirmed, our findings have some implications for the design of active labor market policies. Firstly, cognitive test scores could be a good predictor of human capital that could indeed be easily checked for all unemployed. Secondly, specific tasks on-the-job might contribute to increase cognitive skills for low-school individuals. While the tentative rate of return to on-the-job training that we have estimated is about a third of that of formal schooling, the costs of increasing school attendance for prime aged workers may be substantial. Thirdly, not all sectors have the same ability content for basic educated workers and their differences might shape the direction of job training.

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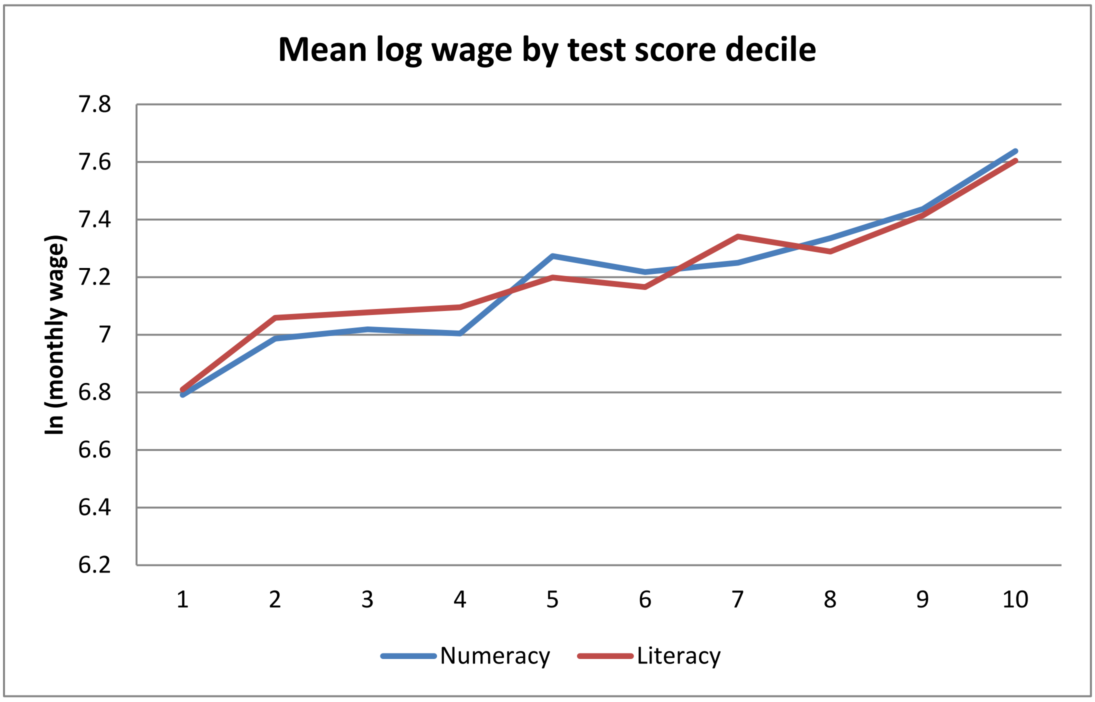
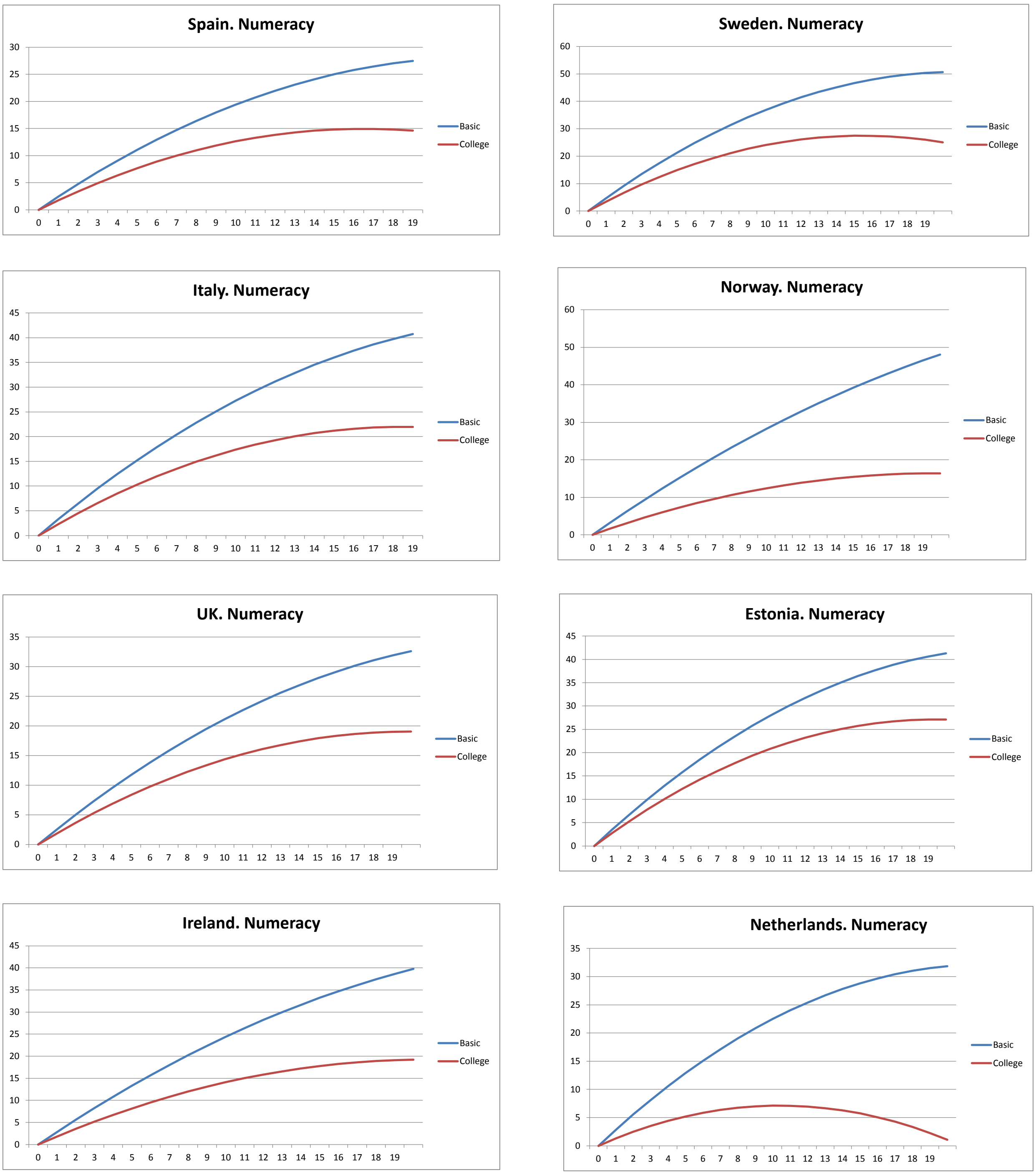
Figure 1: Wage earnings and cognitive skills



Source: PIAAC

Figure 2: The impact of working experience on numeracy scores, by country



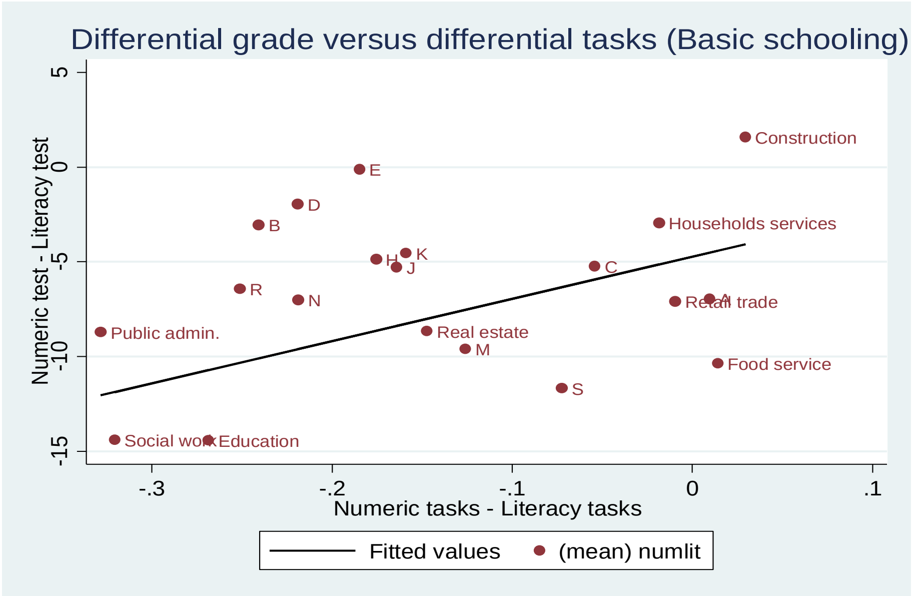
Source: PIAAC
Footnotes:

a. Each graph shows for each country how the predicted numeracy score varies with working experience, for an individual with a college degree (blue line) and another with basic schooling (red line). The prediction is for a single male aged between 40 and 45 years of age, with fair health and no interest in learning new things. The prediction is obtained using the estimated coefficients shown in Table 3.

b. To permit comparisons along the life cycle, the numerical score for 0 years of experience is normalized to zero for each schooling group.

c. Numeracy scores are not adjusted for the country-specific standard deviation.

Figure 3: Differential grade versus differential tasks by industry (Basic schooling)



Source: PIAAC

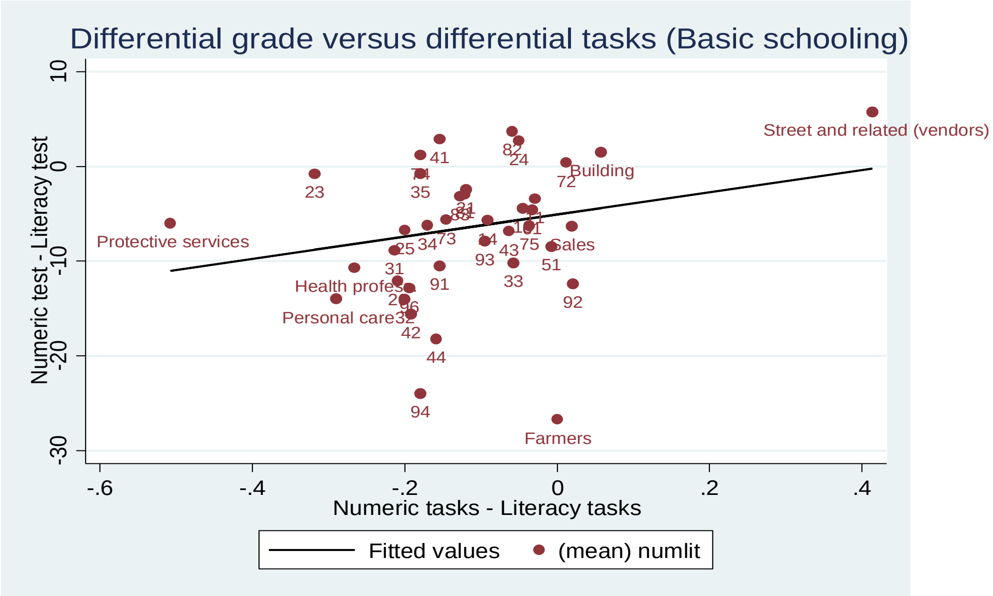
Footnotes:

a. Sample includes respondents of 26 to 45 years old (PIAAC database) with basic schooling.

b. Only representative countries are considered (Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands).

c. The differential grade between numeric test and literacy test is presented in the Y axis, while the X axis presents the difference between the proportion of numeric tasks done at least during the last month over all plausible numeric tasks and the proportion of literacy tasks done at least during the last month over the all plausible literacy tasks.

Figure 3B: Differential grade versus differential tasks by occupation (Basic schooling)



Source: PIAAC

Footnotes:

a. Sample includes respondents of 26 to 45 years old (PIAAC database) with basic schooling.

b. Only representative countries are considered (Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands).

c. The differential grade between numeric test and literacy test is presented in the Y axis, while the X axis presents the difference between the proportion of numeric tasks done at least during the last month over all plausible numeric tasks and the proportion of literacy tasks done at least during the last month over the all plausible literacy tasks.

Table 1: Summary statistics

Summary Statistics		FULL SAMPLE	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
Numeracy test (mean)	Basic	230.7	224.5	229.5	225.0	214.3	245.5	217.1	240.4	248.9
	Bachelor	269.2	254.8	265.3	260.3	256.3	279.7	279.1	270.9	287.1
	College	297.2	280.3	283.6	289.7	288.3	311.3	312.8	295.2	316.7
Literacy test (mean)	Basic	240.6	231.4	234.5	242.0	230.3	257.1	223.4	247.5	258.8
	Bachelor	273.8	257.9	264.5	273.4	267.9	279.6	281.1	273.1	292.8
	College	300.4	284.6	283.6	299.4	295.0	309.3	312.7	297.2	321.2
Working experience (mean)		13.8	12.6	13.3	14.7	13.9	14.1	13.2	13.5	15.0
Fraction of males		47.4	49.7	48.8	39.9	45.5	50.7	51.3	46.5	46.9
Fraction with basic schooling		19.8	41.3	29.7	20.3	15.3	12.9	7.8	12.6	18.6
Fraction with bachelor degree (high school)		38.4	20.0	49.0	35.5	38.4	34.8	45.1	43.5	41.4
Fraction with a college degree		41.8	38.7	21.3	44.3	46.3	52.4	47.1	43.9	40.0

Source: PIAAC. Population 26-45 years old.
Footnotes:
a. Full sample includes respondents from Spain, Italy, Great Britain, Ireland, Norway, Sweden, Estonia and the Netherlands
b. The standard deviation of the numeracy score is 52.18 (full sample) and that of the literacy score is 47.43. Both measures are for the full sample.

Table 2: Tasks by country of residence and level of education

Level of education	FULL SAMPLE	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
				Basic numeracy tasks					
Basic	30.84	31.30	35.50	28.13	22.82	36.69	32.26	30.08	29.91
Bachelor	32.40	33.40	34.62	32.36	33.10	33.63	36.77	25.29	29.99
College	19.39	19.94	22.73	18.88	21.36	18.25	21.97	13.56	18.44
				Advanced numeracy tasks					
Basic	19.34	13.43	8.14	16.37	11.63	28.63	23.39	28.46	24.63
Bachelor	41.50	33.21	32.25	37.69	28.19	50.07	45.68	53.50	51.39
College	68.68	61.40	57.27	68.97	62.60	75.00	72.17	77.55	74.45
Obs.	19738	2617	2065	3862	2921	1925	1593	2925	1830

Level of education	FULL SAMPLE	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
				Basic literacy tasks					
Basic	29.61	30.19	27.2	29.03	27.07	22.58	24.19	38.21	38.42
Bachelor	27.30	37.02	29.77	28.12	32.02	14.05	19.36	32.29	25.76
College	11.29	20.24	12.95	13.5	15.23	4.56	6.79	8.73	8.33
				Advanced literacy tasks					
Basic	29.45	18.89	17.75	23.53	17.23	56.45	38.71	28.73	34.31
Bachelor	54.44	36.64	44.81	50.11	37.73	79.07	70.61	51.53	64.99
College	81.63	66.54	76.59	78.02	74.28	92.76	90.81	85.5	88.52
Obs.	19738	2617	2065	3862	2921	1925	1593	2925	1830

Source: PIAAC

Footnotes:

a. The sample contains respondents that are 26 to 45 years old at the time of the interview.

b. Each entry is the percentage of respondent reporting having performed at least one task during the last month in their current or last job. Tasks are grouped depending on the level of its difficulty, both by our own assessment and by the results of a principal component analysis -see text.

Basic numeracy tasks: elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams.

Advanced numeracy tasks: elaborating graphs or using algebra.

Basic literacy tasks: reading email, reading guides, reading manuals, writing emails, writing reports, reading articles

Advanced literacy tasks: reading academic hournals, reading books and writing articles.

c. The full sample includes Spain, Italy, Great Britain, Ireland, Norway, Sweden, Estonia and Netherlands

Table 3: The link between years of working experience and numeracy test scores (parametric analysis)

Parametric analysis	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
1. Working experience - 15	0.842***	1.436***	1.147***	1.538***	1.985***	1.384***	1.339***	0.936**
	(0.195)	(0.230)	(0.236)	(0.332)	(0.480)	(0.517)	(0.342)	(0.396)
2. (Working experience - 15)*Bachelor	-0.236	0.0700	-0.0501	-0.621	-0.870*	-0.000913	-0.393	-0.575
	(0.342)	(0.301)	(0.287)	(0.378)	(0.520)	(0.530)	(0.372)	(0.432)
3. (Working experience - 15)*College	-0.677**	-0.987**	-0.676**	-1.028***	-1.584***	-1.280**	-0.711*	-1.539***
	(0.266)	(0.440)	(0.282)	(0.369)	(0.487)	(0.539)	(0.376)	(0.419)
4. (Working experience - 15)^2	-0.0549***	-0.0643***	-0.0482***	-0.0451***	-0.0419**	-0.115***	-0.0726***	-0.0657***
	(0.0121)	(0.0158)	(0.0120)	(0.0156)	(0.0213)	(0.0220)	(0.0185)	(0.0195)
Obs.	2,612	2,612	3,859	2,612	1,924	1,590	2,921	1,830
R2	0.401	0.401	0.372	0.401	0.434	0.516	0.252	0.386

Source: PIAAC (respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and the Netherlands)

Footnotes:

a. The sample contains respondents 26 to 45 years old. The dependent variable is the numeracy score (measured from 0 to 500)

All models include as regressors (not shown) a dummy for female, two dummies with the education level of the respondent (omitted value: basic schooling), a dummy that takes value one if respondent is not working, two dummies with the level of education of the mother (bachelor and college), a dummy that takes value 1 if foreign born, another for married, 4 dummies with 5-year age bands, a dummy for exam done on paper, one dummy for poor health, another for "enjoy learning new things", and a final one for no work experience.

b. Experience is the deviation of the number of years worked full time minus 15. The specification in Table 3 assumes that the estimate of (experience-15) squared is common across all education groups. The assumption is relaxed in Table 3B.

The estimates shown are the coefficients of experience, where the omitted group is basic schooling. Heteroscedasticity-adjusted standard errors in parentheses.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 3B: The link between years of working experience and numeracy test scores (semiparametric analysis)

	Years	SP	IT	GB	IL	NO	SW	ES	NL
Basic schooling	**0**	8.046***	3.179*	5.227***	6.282***	7.284***	n.a.	0.318	n.a.
		(1.375)	(1.766)	(1.181)	(1.770)	(1.934)		(2.684)	
	10	2.785***	-0.146	4.090***	4.298***	4.704***	n.a.	1.378	n.a.
		(0.897)	(0.971)	(0.755)	(1.247)	(1.142)		(0.839)	
	15	0.874**	0.475	1.131*	2.987***	2.907***	n.a.	-3.127**	n.a.
		(0.431)	(0.757)	(0.587)	(0.968)	(0.777)		(1.396)	
Obs.		530	288	306	199	136		201	
Bachelor	**0**	3.077	2.400	1.635	1.024	4.958*	4,199	0.964	n.a.
		(2.141)	(1.572)	(2.844)	(1.834)	(2.811)	(2.569)	(1.180)	
	10	0.620	2.266***	2.633***	2.005***	1.440	1.647***	0.591	n.a.
		(0.782)	(0.727)	(0.943)	(0.649)	(1.121)	(0.628)	(0.521)	
	15	0.920	1.056*	1.167**	1.681***	0.782	1.707***	-0.0158	n.a.
		(0.674)	(0.578)	(0.562)	(0.559)	(0.771)	(0.500)	(0.471)	
Obs.		261	485	523	492	393	417	678	
College	**0**	1.441	0.926	5.038***	-0.514	6.389**	2.796	2.930	0.127
		(2.498)	(2.988)	(1.592)	(1.526)	(2.727)	(2.966)	(2.225)	(1.905)
	10	0.115	0.719	0.870*	1.007*	0.970	1.184	0.738	-1.225*
		(0.470)	(1.044)	(0.464)	(0.520)	(0.699)	(0.772)	(0.783)	(0.702)
	15	-0.247	-1193	-0.175	0.167	-0.175	0.205	-1.179*	-0.714
		(0.612)	(1.162)	(0.544)	(0.496)	(0.499)	(0.643)	(0.711)	(0.593)
Obs.		452	169	629	551	442	332	464	346

Source: PIAAC (respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and the Netherlands)
Footnotes: a. The sample is composed of respondents 26 to 45 years old. The dependent variable is the numeracy score (measured from 0 to 500)
b. The coefficients shown are the impact of an additional year of experience on the numeracy score, estimated for different years of experience.
The semiparametric analysis is estimated using local polynomial regressors for each year of experience using a common bandwidth of 0.8 years
The covariates listed in Table 3 are included linearly and then partialed out as in Robinson (1988). The standard errors are bootstrapped 50 times.
c. n.a. on a cell means that the subsample was too small to conduct a semiparametric estimation

Table 4: Numerical tasks in the last/current job and numeracy test scores, by schooling group

Variables	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
1. Basic tasks$_{Num}$	**6.833****	**8.831****	**11.20****	**15.38****	**15.06***	**19.07***	**3.188**	**12.21****
	(3.108)	(4.417)	(4.479)	(6.756)	(8.224)	(10.79)	(5.541)	(5.871)
2. Basic tasks$_{Num}$*Bachelor	-2.953	-0.625	-3.155	-4.687	-7.888	-13.07	3.172	-7.860
	(6.030)	(5.637)	(5.544)	(7.749)	(9.909)	(11.98)	(6.571)	(7.376)
3. Basic tasks$_{Num}$*College	-3.395	3.039	-3.406	-5.966	-4.573	-0.946	3.232	-4.386
	(4.636)	(7.600)	(5.952)	(7.736)	(10.79)	(12.59)	(7.485)	(7.903)
4. Advanced tasks$_{Num}$	**7.182****	**12.29****	**6.918**	**8.300**	**29.47*****	**13.23**	**11.63****	**19.38*****
	(3.636)	(5.484)	(4.613)	(7.067)	(6.207)	(11.56)	(5.074)	(5.498)
5. Advanced tasks$_{Num}$*Bachelor	2.558	5.059	9.951*	0.962	-14.03*	-1.634	-0.242	2.759
	(5.719)	(6.224)	(5.271)	(7.738)	(7.182)	(12.08)	(5.637)	(6.190)
6. Advanced tasks$_{Num}$*College	8.543*	8.122	7.419	10.36	-9.556	3.781	1.594	-9.466
	(4.566)	(7.187)	(5.234)	(7.500)	(7.000)	(12.05)	(5.977)	(6.433)
Obs.	2,612	2,061	3,859	2,917	1,924	1,590	2,921	1,830
R2	0.429	0.322	0.403	0.376	0.486	0.552	0.293	0.445

Source: PIAAC

Footnotes:

a. Sample contains respondents aged 26 to 45 years old

b. The dependent variable is the score in the numeracy test, measured from 0 to 500 -it is not normalized. The estimated method is OLS.

Additional regressors (not shown) are: working experience minus 12, and its interaction with dummies of bachelor and college as well as all the covariates listed in Table b. The dummy "Basic tasks Num" takes value 1 if the respondent reports having performed at least one numerical task at least once a month in his or her current or last job and zero otherwise.

The "basic numeracy tasks" include elaborating a budget, using a calculator, reading bills, using fractions or reading diagrams.

The "advanced numeracy tasks" include having generated graphs or using algebra.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 4B: Literacy tasks in the last/current job and literacy test scores, by schooling group

Variables	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
Basic tasks$_{Lit}$	**7.250****	**9.945****	**3.893**	**20.45*****	**21.07***	**30.84*****	**4.368**	**10.25**
	(3.016)	(4.036)	(6.033)	(7.407)	(12.13)	(10.50)	(5.846)	(7.564)
Basic tasks$_{Lit}$*Bachelor	-5.195	5.161	-6.226	-11.37	-20.37	-29.23**	5.771	-9.653
	(5.859)	(5.815)	(7.813)	(8.951)	(15.44)	(12.34)	(7.068)	(10.78)
Basic tasks$_{Lit}$*College	-0.355	5.157	-0.627	-11.26	-8.681	1.784	-10.36	7.104
	(5.559)	(10.83)	(8.388)	(8.812)	(17.92)	(14.84)	(8.938)	(14.87)
Advanced tasks$_{Lit}$	**6.339***	**5.130**	**1.828**	**-5.671**	**13.33***	**0.830**	**-8.718***	**19.79*****
	(3.304)	(4.440)	(4.077)	(5.688)	(7.339)	(10.35)	(4.912)	(4.703)
Advanced tasks$_{Lit}$*Bachelor	-4.283	0.262	7.761	10.21	-8.883	2.948	12.39**	-13.96**
	(5.171)	(5.236)	(4.788)	(6.308)	(8.887)	(11.15)	(5.458)	(5.577)
Advanced tasks$_{Lit}$*College	9.958**	2.603	7.154	15.84**	-1.044	7.570	25.22***	-14.66**
	(4.509)	(6.758)	(4.846)	(6.363)	(9.990)	(12.07)	(6.139)	(6.385)
Obs.	2,612	2,061	3,859	2,917	1,924	1,590	2,921	1,830
R squared	0.373	0.259	0.331	0.318	0.404	0.529	0.241	0.384

Source: PIAAC
Footnotes:
a. Sample contains respondents aged 26 to 45 years old
b. The dependent variable is the score in the literacy test, measured from 0 to 500 -it is not normalized. The estimated method is OLS.
Additional regressors (not shown) are: working experience minus 12, and its interaction with dummies of bachelor and college as well as all the covariates listed in Table 3
b. The dummy "Basic tasks$_{Lit}$" (Advanced tasks$_{Lit}$) takes value 1 if the respondent reports having performed at least one basic (advanced) task at least once
a month in his or her current or last job and zero otherwise.
"Basic literacy tasks" include reading email, reading guides, reading manuals, writing emails, wirting reports, reading articles
"Advanced literacy tasks" include reading academic hournals, reading books and writing articles.
***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 5: The impact of task specialization on relative performance in numeracy and literacy score (All countries pooled)

	Dependent variable: (Numeracy test-Literacy test)					
	Main Sample (ES, IT, GB, IL, NO, SWE, EE, NL)					
Variables	Sample with respondents between 16-65 years of age			Sample with respondents between 16-45 years of age		
(Numeracy-Literacy tasks)	0.225***	0.221***	0.187***	0.229***	0.223***	0.198***
	(0.0229)	(0.0230)	(0.0234)	(0.0293)	(0.0294)	(0.0300)
(Numeracy-Literacy tasks)*Bachelor	-0.105***	-0.108***	-0.105***	-0.118***	-0.122***	-0.115***
	(0.0253)	(0.0254)	(0.0255)	(0.0322)	(0.0322)	(0.0325)
(Numeracy-Literacy tasks)*College	-0.0547**	-0.0626**	-0.0604**	-0.0784**	-0.0849**	-0.0831**
	(0.0270)	(0.0273)	(0.0272)	(0.0337)	(0.0341)	(0.0341)
Obs.	21,965	21,965	21,965	12,872	12,872	12,872
R2	0.108	0.112	0.114	0.090	0.094	0.096
Country dummies	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Occupation dummies	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES

Source: PIAAC (respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and the Netherlands)

Footnotes: a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test, each normalized by its standard deviation.

The independent variable is the individual-specific difference between the frequency of numeracy and literacy tasks performed in the job.

Numeric task is the fraction of numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of literacy tasks reported.

The difference between "numeric" and "literacy task" is the degree of specialization in one type of tasks. It takes value 1 if the individual performs *all* numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5 year bands)

In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 5B: The impact of task specialization on relative performance in numeracy and literacy score (All countries pooled)

	Dependent variable: (Numeracy test-Literacy test)					
	Extended sample (main sample + 6 extra countries)					
Variables	Sample with respondents between 16-65 years of age			Sample with respondents between 16-45 years of age		
(Numeracy-Literacy tasks)	0.207***	0.206***	0.169***	0.199***	0.199***	0.164***
	(0.0198)	(0.0199)	(0.0202)	(0.0264)	(0.0266)	(0.0270)
(Numeracy-Literacy tasks)*Bachelor	-0.0903***	-0.0956***	-0.0873***	-0.0839***	-0.0921***	-0.0793***
	(0.0208)	(0.0208)	(0.0209)	(0.0273)	(0.0274)	(0.0275)
(Numeracy-Literacy tasks)*College	-0.0764***	-0.0833***	-0.0759***	-0.0631**	-0.0695**	-0.0618**
	(0.0236)	(0.0240)	(0.0238)	(0.0302)	(0.0305)	(0.0304)
Obs.	35,782	35,782	35,782	20,923	20,923	20,923
R2	0.071	0.073	0.075	0.057	0.059	0.061
Country dummies	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Occupation dummies	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES

Source: PIAAC (respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia, the Netherlands, Czech Republic, France, Finland, Korea, Russia and Slovak Republic)

Footnotes: a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test normalized by standard deviation.

The independent variable is the difference between two variables: numeracy tasks and literacy tasks. It takes value 1 if the individual reported having performed all tasks.

Numeric task is the fraction of numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of literacy tasks reported.

The difference between "numeric" and "literacy task" is the degree of specialization in one type of tasks. It takes value 1 if the individual performs *all* numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5 year bands)

In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

c. Main sample contains respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands.

d. The extended sample also includes workers in the Czech Republic, France, Finland, Korea, Russia and Slovak Republic.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 6: The impact of task specialization on relative performance in numeracy and literacy score (All countries pooled)

Variables	Dependent variable: (Numeracy test-Literacy test)					
	Main Sample (ES, IT, GB, IL, NO, SWE, EE, NL)					
	Sample with respondents between 16-65 years of age			Sample with respondents between 16-45 years of age		
(Numeracy-Literacy tasks)$_{basic}$	0.118***	0.108***	0.0985***	0.0905***	0.0790***	0.0640**
	(0.0343)	(0.0343)	(0.0348)	(0.0266)	(0.0267)	(0.0271)
(Numeracy-Literacy tasks)$_{basic}$*Bachelor	-0.0746*	-0.0737*	-0.0769*	-0.0402	-0.0357	-0.0427
	(0.0414)	(0.0414)	(0.0415)	(0.0322)	(0.0323)	(0.0323)
(Numeracy-Literacy tasks)$_{basic}$*College	-0.0535	-0.0567	-0.0587	-0.0133	-0.0140	-0.0176
	(0.0422)	(0.0425)	(0.0426)	(0.0333)	(0.0336)	(0.0337)
(Numeracy-Literacy tasks)$_{advanced}$	0.0615*	0.0545*	0.0490	0.0387	0.0366	0.0299
	(0.0328)	(0.0330)	(0.0328)	(0.0251)	(0.0252)	(0.0252)
(Numeracy-Literacy tasks)$_{advanced}$*Bachelor	0.00288	0.00769	0.00998	0.0319	0.0350	0.0330
	(0.0375)	(0.0375)	(0.0374)	(0.0288)	(0.0288)	(0.0288)
(Numeracy-Literacy tasks)$_{advanced}$*College	0.0449	0.0551	0.0466	0.0820***	0.0862***	0.0771***
	(0.0370)	(0.0371)	(0.0369)	(0.0286)	(0.0286)	(0.0286)
Obs.	12,872	12,872	12,872	10,877	10,877	10,877
R2	0.091	0.095	0.098	0.125	0.128	0.133
Country dummies	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Occupation dummies	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES

Source: PIAAC

Footnotes: a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test normalized by standard deviation.

The independent variable is the difference between two variables: numeracy basic tasks and literacy basic tasks. It takes value 1 if the individual reported having performed all basic tasks.

Numeric task is the fraction of basic numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of basic literacy tasks reported.

The difference between "numeric" and "literacy task" is the degree of specialization in one type of tasks. It takes value 1 if the individual performs *all* basic numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5 year bands)

In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

c. Main sample contains respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 6B: The impact of task specialization on relative performance in numeracy and literacy score (All countries pooled)

Variables	Dependent variable: (Numeracy test-Literacy test)					
	Extended sample (main sample + 6 extra countries)					
	Sample with respondents between 16-65 years of age			Sample with respondents between 16-45 years of age		
(Numeracy-Literacy tasks)$_{basic}$	0.101***	0.0934***	0.0799**	0.0668***	0.0596**	0.0437*
	(0.0337)	(0.0337)	(0.0339)	(0.0236)	(0.0237)	(0.0239)
(Numeracy-Literacy tasks)$_{basic}$*Bachelor	-0.0430	-0.0439	-0.0435	-0.0151	-0.0149	-0.0171
	(0.0383)	(0.0383)	(0.0383)	(0.0275)	(0.0275)	(0.0275)
(Numeracy-Literacy tasks)$_{basic}$*College	-0.0391	-0.0390	-0.0404	-0.0193	-0.0205	-0.0216
	(0.0400)	(0.0402)	(0.0401)	(0.0295)	(0.0297)	(0.0296)
(Numeracy-Literacy tasks)$_{advanced}$	0.0584*	0.0557*	0.0482	0.0519**	0.0516**	0.0448**
	(0.0314)	(0.0316)	(0.0314)	(0.0226)	(0.0226)	(0.0226)
(Numeracy-Literacy tasks)$_{advanced}$*Bachelor	-0.0102	-0.00621	-0.00829	0.0157	0.0181	0.0128
	(0.0349)	(0.0349)	(0.0348)	(0.0254)	(0.0254)	(0.0254)
(Numeracy-Literacy tasks)$_{advanced}$*College	0.0313	0.0367	0.0298	0.0545**	0.0564**	0.0485*
	(0.0347)	(0.0348)	(0.0346)	(0.0255)	(0.0255)	(0.0255)
Obs.	20,923	20,923	20,923	35,782	35,782	35,782
R2	0.057	0.060	0.062	0.072	0.074	0.076
Country dummies	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Occupation dummies	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES

Source: PIAAC

Footnotes: a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test normalized by standard deviation.

The independent variable is the difference between two variables: numeracy basic tasks and literacy basic tasks. It takes value 1 if the individual reported having performed all basic tasks.

Numeric task is the fraction of basic numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of basic literacy tasks reported.

The difference between "numeric" and "literacy task" is the degree of specialization in one type of tasks. It takes value 1 if the individual performs *all* basic numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5 year bands)

In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

c. Main sample contains respondents in Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands.

d. The extended sample also includes workers in the Czech Republic, France, Finland, Korea, Russia and Slovak Republic.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table A1: Percentages of people doing all basic or advanced numeracy and literacy tasks

Level of education	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
				Basic numeracy tasks				
Basic	15.56	13.36	16.75	15.21	26.61	18.55	13.82	15.25
Bachelor	24.43	23.94	24.4	24.26	29.9	32.73	21.29	25.76
College	18.95	21.82	25.48	23.8	23.61	29.16	16.99	19.13
				Advanced numeracy tasks				
Basic	4.44	3	5.88	2.91	12.5	10	6.78	10.56
Bachelor	16	17.61	18.99	13.56	28.1	24.09	26.71	26.16
College	39.39	37.05	44.42	38.36	51.29	50.07	58.61	56.01
Obs.	2617	2065	3862	2921	1925	1593	2925	1830

Level of education	SPAIN	ITALY	GREAT BRITAIN	IRELAND	NORWAY	SWEDEN	ESTONIA	NETHERLANDS
				Basic literacy asks				
Basic	0.74	1	2.43	1.57	3.63	4	0.27	5.57
Bachelor	3.24	5.54	6.87	3.84	7.92	10.03	6.28	10.96
College	11.94	17.05	27.7	16.85	20.63	25.03	25.18	36.61
				Advanced literacy tasks				
Basic	0	0	0	0	0	0	0	0
Bachelor	0	0	0	0	0	0	0	0
College	0	0	0	0	0	0	0	0
Obs.	2617	2065	3862	2921	1925	1593	2925	1830

Source: PIAAC
Footnotes:
a. Sample is composed of people of 26 to 45 years old (PIAAC database).
b. Numbers of the tables mean the percentage of people doing all tasks of the same group during the last month. Tasks are grouped depending on the level of difficulty and the type of subject.
Basic numeracy tasks: elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams.
Advanced numeracy tasks: elaborating graphs or using algebra.
Basic literacy tasks: reading email, reading guides, reading manuals, writing emails, writing reports, reading articles
Advanced literacy tasks: reading academic hournals, reading books and writing articles.

Table A2: Frequency of numeracy and literacy tasks (basic schooling)

INDUSTRY (ISIC CLASSIFICATION)	Share of workers (basic schooling)	PCA numeracy	PCA literacy	BASIC NUMERACY TASKS				BASIC LITERACY		
				Elaborate budgets	Use calculator	Use fractions	Read diagrams	Read emails	Read guides	Write emails
		(scaled 0-1)		(Relative to the average)				(Relative to the average)		
A Agriculture, forestry and fishing	6.130	0.102	0.096	1.030	0.796	0.777	0.502	0.494	0.687	0.555
B Mining and quarrying	0.308	0.126	0.191	0.284	0.856	0.606	1.998	0.741	1.112	0.866
C Manufacturing	18.116	0.156	0.136	0.532	1.107	0.871	1.025	0.656	0.990	0.615
D Electricity, gas, steam and air conditioning supply	0.308	0.305	0.378	1.422	1.070	2.121	1.713	1.483	1.112	1.300
E Water supply; sewerage, waste management and remediation activ	0.993	0.105	0.179	0.618	0.731	0.752	0.975	0.863	1.036	0.672
F Construction	13.116	0.170	0.134	1.103	1.127	1.218	1.543	0.723	1.046	0.651
G Wholesale and retail trade; repair of motor vehicles and motorcycl	17.979	0.206	0.191	1.463	1.266	1.200	0.754	0.966	1.013	0.821
H Transportation and storage	6.027	0.141	0.190	0.640	0.974	0.651	1.182	0.929	1.040	0.875
I Accommodation and food service activities	7.877	0.146	0.126	1.224	0.863	0.806	0.302	0.573	0.765	0.568
J Information and communication	1.164	0.288	0.363	1.731	1.530	1.444	1.587	1.570	1.304	1.777
K Financial and insurance activities	0.753	0.437	0.407	1.512	1.751	2.108	1.285	1.592	1.365	1.772
L Real estate activities	0.411	0.264	0.323	1.493	1.284	1.364	1.499	1.390	1.192	1.462
M Professional, scientific and technical activities	1.507	0.266	0.326	1.687	1.532	1.798	1.168	1.555	1.170	1.684
N Administrative and support service activities	5.925	0.079	0.158	0.533	0.624	0.536	0.772	0.791	0.934	0.721
O Public administration and defence; compulsory social security	3.390	0.132	0.296	0.776	0.837	0.606	1.375	1.365	1.084	1.359
P Education	2.055	0.070	0.192	0.384	0.706	0.636	0.557	0.918	0.930	0.845
Q Human health and social work activities	7.363	0.077	0.217	0.560	0.690	0.558	0.609	1.094	1.071	1.061
R Arts, entertainment and recreation	2.055	0.136	0.223	1.066	0.899	0.818	0.642	1.084	1.049	1.137
S Other service activities	2.774	0.153	0.168	1.390	1.094	0.808	0.412	0.886	0.848	0.915
T Activities of households as employers; undifferentiated goods.	1.747	0.035	0.053	0.552	0.264	0.321	0.101	0.327	0.252	0.344
Mean		0.170	0.217	1	1	1	1	1	1	1
Minimum		0.035	0.053	0.284	0.264	0.321	0.101	0.327	0.252	0.344
Maximum		0.437	0.407	1.731	1.751	2.121	1.998	1.592	1.365	1.777

Source: PIAAC
Footnotes:

a. Sample is composed of people of 16 to 45 years old (PIAAC database) from representative countries (Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands) only with basic schooling.

b. Tasks has been summarized using Principal Componen Analysis. Main numeacy tasks are use fractions (0.43), use calculator (0.42), elaborate budgets (0.37), read bills (0.33) and read diagrams (0.28). Main literacy tasks are read emails (0.42), write emails (0.40) and read guides (0.32).

Table A3: Frequency of numeracy and literacy tasks (basic schooling)

OCCUPATION (ISCO CLASSIFICATION)	Share of workers (basic schooling)	PCA numeracy	PCA literacy	BASIC NUMERACY TASKS				BASIC LITERACY		
				Elaborate budgets	Use calculator	Use fractions	Read diagrams	Read emails	Read guides	Write emails
		(scaled 0-1)		(Relative to the average)				(Relative to the average)		
11 Chief executives, senior officials and legislators	0.440	0.276	0.287	0.000	1.740	2.104	0.863	0.000	1.493	0.000
12 Administrative and commercial managers	0.720	0.442	0.422	2.291	0.000	2.057	1.845	2.050	1.551	1.940
13 Production and specialised services managers	1.401	0.317	0.338	2.149	1.696	1.785	1.491	1.985	1.360	1.760
14 Hospitality, retail and other services managers	1.881	0.339	0.316	1.910	1.711	1.576	0.656	1.940	1.432	1.529
21 Science and engineering professionals	0.200	0.349	0.339	1.456	1.149	1.851	1.898	0.000	0.000	1.643
22 Health professionals	0.200	0.133	0.347	1.941	0.766	0.926	1.423	0.000	1.313	0.000
23 Teaching professionals	0.360	0.108	0.228	0.809	0.638	0.771	0.791	1.447	1.095	1.141
24 Business and administration professionals	0.480	0.386	0.417	1.819	1.595	1.736	1.779	1.809	0.000	1.882
25 Information and communications technology professionals	0.400	0.384	0.507	1.941	0.000	1.620	2.135	0.000	1.478	1.848
26 Legal, social and cultural professionals	0.360	0.169	0.401	1.348	1.064	1.286	1.318	1.930	1.277	1.825
31 Science and engineering associate professionals	1.561	0.243	0.326	0.871	1.522	1.306	1.703	1.781	1.473	1.632
32 Health associate professionals	0.800	0.178	0.256	0.849	1.053	1.157	1.067	1.303	1.478	1.027
33 Business and administration associate professionals	2.641	0.348	0.380	1.875	1.740	1.683	1.474	2.007	1.368	1.836
34 Legal, social, cultural and related associate professionals	1.361	0.193	0.255	1.356	0.901	1.021	0.767	1.341	1.207	1.148
35 Information and communications technicians	0.240	0.235	0.392	1.617	1.595	1.543	1.581	0.000	1.095	0.000
41 General and keyboard clerks	0.080	0.206	0.262	1.248	1.367	0.727	0.746	2.109	1.173	1.819
42 Customer services clerks	1.401	0.268	0.337	1.266	1.373	1.207	0.825	1.935	1.392	1.607
43 Numerical and material recording clerks	1.841	0.236	0.227	1.115	1.320	1.250	0.791	1.397	1.170	1.275
44 Other clerical support workers	3.481	0.249	0.309	1.115	1.552	1.188	0.962	1.819	1.376	1.665
51 Personal service workers	1.481	0.133	0.136	1.213	0.947	0.649	0.290	0.875	0.896	0.660
52 Sales workers	7.843	0.204	0.171	1.574	1.344	0.954	0.542	1.249	1.146	0.813
53 Personal care workers	9.804	0.054	0.197	0.416	0.580	0.410	0.474	1.303	1.051	0.986
54 Protective services workers	7.003	0.085	0.301	0.527	0.624	0.252	0.980	1.510	1.463	1.384
61 Market-oriented skilled agricultural workers	1.841	0.116	0.141	1.431	1.031	0.860	0.669	1.169	1.074	1.027
62 Market-oriented skilled forestry, fishery and hunting workers	3.121	0.140	0.128	0.809	0.893	0.926	0.791	0.579	0.438	0.685
63 Subsistence farmers, fishers, hunters and gatherers	0.600	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
71 Building and related trades workers, excluding electricians	0.040	0.153	0.118	1.028	1.062	0.990	1.202	0.863	1.104	0.610
72 Metal, machinery and related trades workers	0.040	0.176	0.164	0.767	1.194	0.910	1.440	0.891	1.221	0.702
73 Handicraft and printing workers	9.164	0.186	0.220	0.539	1.276	0.900	0.791	0.724	1.186	0.570
74 Electrical and electronic trades workers	4.682	0.165	0.234	0.866	1.367	1.075	1.949	1.473	1.525	1.027
75 Food processing, wood working, garment and other craft	0.720	0.114	0.085	0.749	0.788	0.545	0.314	0.798	0.869	0.544
81 Stationary plant and machine operators	1.120	0.114	0.137	0.299	0.922	0.657	0.820	0.831	1.074	0.659
82 Assemblers	2.721	0.127	0.101	0.105	0.916	0.704	1.135	0.661	0.999	0.536
83 Drivers and mobile plant operators	3.241	0.140	0.171	0.644	0.847	0.591	1.198	1.063	1.266	0.674
91 Cleaners and helpers	0.920	0.021	0.065	0.223	0.147	0.083	0.194	0.609	0.670	0.377
92 Agricultural, forestry and fishery labourers	7.683	0.027	0.021	0.418	0.297	0.279	0.164	0.037	0.368	0.071
93 Labourers in mining, construction, manufacturing and transport	7.843	0.089	0.120	0.501	0.740	0.478	0.554	0.753	0.974	0.507
94 Food preparation assistants	2.321	0.075	0.095	0.871	0.442	0.356	0.182	0.779	0.884	0.737
95 Street and related sales and service workers	6.002	0.219	0.030	0.000	0.957	1.157	0.000	0.000	0.000	0.000
96 Refuse workers and other elementary workers	1.561	0.075	0.128	0.428	0.450	0.499	0.837	0.979	1.062	0.604
Mean		0.114	0.131	1	1	1	1	1	1	1
Minimum		0.000	0.000	0	0	0	0	0	0	0
Maximum		0.219	0.301	2.291	1.740	2.104	2.135	2.109	1.551	1.940

Source: PIAAC

Footnotes:

a. Sample is composed of people of 16 to 45 years old (PIAAC database) from representative countries (Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands) only with basic schooling.

b. Tasks has been summarized using Principal Componen Analysis. Main numeacy tasks are: use fractions (0.43), use calculator (0.42), elaborate budgets (0.37), read bills (0.33) and read diagrams (0.28). Main literacy tasks are: read emails (0.42), write emails (0.40) and read guides (0.32).