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Abstract

We study how formal education and experience in the labour market correlate with measures of human capital available in thirteen countries participating in the Program for the International Assessment of Adult Competences (PIAAC), an international study assessing adults' proficiency in numeracy and literacy. Two findings are consistent with the notion that, in producing human capital, work experience is a substitute for formal education for respondents with compulsory schooling. Firstly, the number of years of working experience correlates with performance in PIAAC mostly among low-educated individuals. Secondly, individual fixed-effect models suggest that workers in jobs intensive in numerical tasks – relative to reading tasks – perform relatively better in the numeracy section of the PIAAC test than in the reading part. The results are driven by young individuals with low levels of schooling and hold mainly for simple tasks, suggesting that our findings are not fully generated by the sorting of workers across jobs. A back-of-the-envelope estimate suggests that the contribution of on-the-job learning to skill formation is a quarter of that of compulsory schooling in the countries we analyse.

Keywords: human capital, tasks, education, working experience, cognitive skills.

JEL classification: J24, J31, I20.

Resumen

En este documento se analiza la forma en que la educación académica y la experiencia profesional correlacionan con el nivel de capital humano, medido por la capacidad cognitiva demostrada en diferentes exámenes numéricos y de comprensión lectora según los datos de la OCDE obtenidos para el estudio PIAAC en 13 países. Se obtienen dos resultados principales. En primer lugar, la experiencia laboral correlaciona con los resultados de los exámenes, especialmente para los individuos de baja cualificación. En segundo lugar, a través de un modelo de efectos fijos que permite controlar por la habilidad inicial de los individuos, se comprueba que los individuos con trabajos intensivos en tareas numéricas en comparación con tareas de comprensión lectora obtienen mejores resultados relativos en el test numérico. Estos resultados se han obtenido principalmente entre individuos jóvenes con bajo nivel de cualificación, lo que hace suponer que la autoselección de los individuos en distintos trabajos desempeña un papel menor. Con estos resultados, se podría argumentar que la contribución del aprendizaje en el puesto de trabajo a la formación de habilidades podría llegar a ser una cuarta parte de la que aporta la educación obligatoria en la muestra de países que se utiliza en nuestro análisis.

Palabras clave: capital humano, tareas, educación, experiencia laboral, habilidades cognitivas.

Códigos JEL: J24, J31, I20.

1. Introduction

Human capital, defined as the cognitive skills that can be acquired in the formal education system and by learning on-the-job, plays a crucial role in shaping labour market outcomes.[1] Since the seminal study of Mincer (1974) the role of experience and education has been measured using earnings equations that relate the individuals' labour 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 decision to participate in the labour market. 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 labour 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 instrumental variables or natural experiments[2]. The results from that literature generally confirm that education and work experience increase cognitive skills and labour market outcomes beyond their relationship with other unobserved individual characteristics (Card, 1999, Angrist and Krueger, 1991, Carneiro et al., 2011).

Our study uses an alternative route and draws on new data to estimate the contribution of on-the-job training to several measures of cognitive ability of representative samples of the population of thirteen countries participating in PIAAC, an OECD-coordinated effort to measure the skills of the population between 16 and 65 years of age. We focus on how numeracy and reading skills are acquired by individuals who have only completed compulsory education, a group whose labour market outcomes at the time PIAAC was conducted were significantly worse than those of the average worker, and to which a great deal of policy attention has been directed.[3]

By focusing on measures of cognitive abilities as a measure of human capital we can abstract from several of the econometric issues that arise because wages are only available for employees, as numeracy and reading measures are available for a representative sample of the population, including the long-term unemployed. Furthermore, previous studies have documented that the skills measured in PIAAC (or similar assessments) predict ºlabour market outcomes. For example, Leuven et al. (2004) use international data to document that cross-country variation in the net supply of skills -as measured by the International Adult Literacy Survey- correlates negatively correlated with wages. The relationship is especially strong among low-skilled workers, indicating that the skills we measure are indeed priced by the market. Hanushek et al. (2015) also document that numeracy skills are positively associated to

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[1] See Rosen (1972).
[2] See Card (1994) or Murnane et al. (1995).
[3] 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).

wage in the twenty-three countries participating in PIAAC. Understanding then how those skills are shaped by on-the-job learning gives insights about relevant labour market outcomes.

We start by measuring the correlation between the performance in numerical part of PIAAC and on-the-job learning measured as 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 labour market which, in turn, may affect cognitive skills[4]. 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[5]. Using both parametric and non-parametric methods, we document that, in eight countries with large enough samples, early labour market experience correlates strongly with the numeracy score of respondents with compulsory schooling. Interestingly, the link is much weaker among respondents with either a high school or a college degree, contrary to the common perception that labour markets exacerbate pre-existing differences in skills.

However, the extent to which years of working experience increase the cognitive skills of a person can be confounded by unobserved factors, like pre-labour market cognitive or non-cognitive skills[6]. For that reason, we estimate the contribution of on-the-job learning on measures of cognitive skills by drawing on the availability of multiple measures of skills for the same individual and the fact that jobs vary in their task content. Namely, we estimate the effect of the relative intensity of numeracy (versus literacy) tasks on the job on the relative score in numeracy (versus reading) tests, using a specification that absorbs any individual-level characteristic that is constant across human capital measures[7].

The above mentioned estimates control for a fixed-effect that is common across all cognitive measures, but not for pre-labour market differences in preferences for numeracy versus literacy tasks that lead workers to select into jobs with a higher numeracy content, for example. To address that selection bias, 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 relative to literacy tests associated to specialization in basic numeric tasks among college or high-school workers must merely reflect sorting across jobs, allowing us to assess to what extent our estimates are reflect biases due to selection.

Our results can be summarized as follows. Individuals with compulsory schooling and working in jobs with a relatively higher intensity of basic numeracy tasks perform relatively better in numeracy tests than in literacy tests. Namely, respondents with basic schooling who fully specialize in basic numerical tasks on their jobs obtain between 12 and 20% of one standard deviation higher scores in the numeracy test than in the reading test. On the other hand, in our

[4] 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 Bender et al. (2010), Jacobson et al. (1993) and Schmieder et al. (2012).
[5] See Becker (1964) and Ben Porath (1967).
[6] 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).
[7] In a different, but related setting Silva et al. (2012) or Bietenbeck (2014) also exploit the availability of multiple measures of cognitive skills and differential exposure across subjects to estimate the contribution of teaching practices to test scores.

preferred sample of individuals below 45 years of age, the association between specialization in numerical tasks and relative performance in the numerical test is much weaker among individuals with a high school or a college degree, suggesting that at most half of the estimated impact is due to sorting biases. We do not explicitly account for the endogeneity of the decision to get schooling. However, we note that the correlation between specialization in basic numerical tasks and relative score in the numeracy test is similar across respondents with high school and with a college degree, a fact that suggests that biases due to endogeneity of schooling may not be that large.

Overall, our results are consistent with the notion that on-the-job learning by conducting basic numerical or reading tasks is a substitute for formal education for workers with compulsory schooling. We draw on evidence in previous studies to obtain a very tentative estimate of the degree of substitution between formal education and skills acquired on the job.

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 Sections 5 quantifies the link between tasks on-the-job and numeracy and literacy scores. Section 6 discusses how we deal with biases due to sorting. Section 7 discusses the magnitude of the estimates and Section 8 presents the main conclusions.

2. The test

We assume that human capital C is acquired either through formal education S or by the task-content of their job, denoted by J. Individuals may also vary in their initial endowment of human capital, C_0, a measure that summarizes factors related to the innate ability of a worker.

$$C = \alpha_0 + \alpha_1 S + \alpha_2 J + \alpha_3 J * S + C_0 + \varepsilon \qquad (1)$$

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 learnt either at school or through practice on-the-job. In that case, α_3 could be negative.

In practice, we can only observe proxies of human capital, C, such as numeracy or literacy scores in standardized tests. That means that we observe

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

In our case, the variable J can take two values, depending on the exact measure of skills we study: reading (l) or numeracy (n). We use two different measures of the task content of a job J. The first measure only serves to motivate our work and it is the *number of years worked full time*, an indicator of exposure to on-the-job learning. The second measure of J denotes the specific skill content of the current or last job, and reflects whether or not an individual performs *particular tasks with numeracy or literacy content*. In our case, we classify tasks into numerical

(J=n) or reading-related (J=l). Finally, ε_m is an unobserved factor, uncorrelated with the initial amount of human capital C_0, but that reflects the initial endowment of the particular human capital concept C_m.

We focus on the skill gain of workers with basic schooling by examining how the task content of a job (either l or n) correlates with different measures of skills. 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 tasks performed in different jobs. However, we deal with a cross section and that information is not available. Hence, when we use as the regressor of interest the type of tasks performed on the job, we also 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_m. Several reasons lead us to expect that α_2 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. In addition, the process of sorting of individuals across jobs may generate a heterogeneous relationship between tasks and the level of human capital. We illustrate that heterogeneity below.

2.1. Controlling for unobserved heterogeneity.

A problem when estimating model (2) is that we rarely observe repeated measures of human capital, particularly of pre-labour market ability C_0. Most likely, workers with a higher level of pre-market skills (i.e. with levels of C_0 above the mean) will work on average in jobs where a higher level of skills are demanded (i.e., where J is also above its 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-labour 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.

We address the omitted variable bias caused by the fact that C_0 is not observable by exploiting multiple measures of human capital for the same individual. In the case of the PIAAC assessment, two main components of human capital are measured: reading and numeracy, or C_m, m=n,l. Assume that performing numerical tasks on the job has an impact on numeric ability, and that performing literacy tasks on the job has a similar impact on reading ability. In that case, one can see 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 reading tests. 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:

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

Model (3) identifies the impact of tasks performed on-the-job on particular forms of human capital (numeracy vs reading ability) by comparing individuals who have different degrees of specialization in the tasks they perform in their jobs (numeric vs reading tasks, or $n - l$). The advantage of Model (3) over Model (2) is that it holds constant an unobserved individual fixed-effect that reflects generic initial human capital acquired before entering the labour market.

However, workers also sort in the labour market according to their initial endowment of human capital, so workers with an initial ability for numeracy-related jobs may sort into numeracy-intensive jobs. In other words, workers with a higher value of $\varepsilon_n - \varepsilon_l$ (i.e., who have a higher comparative advantage in numeracy tasks) are likely to sort into jobs with a relatively heavier math content –i.e., with a higher level of $[n - l]$. Sorting thus generates a positive correlation between the numeracy content of a job and initial endowment of numerical human capital. To get an estimate of the magnitude of the bias due to sorting, we set up a model along the lines of Roy (1951).

2.2. Biases due to sorting

Assume that jobs are bundles of monetary and non-monetary aspects, the latter being related to the type of tasks they involve (either numeracy- or literacy related tasks).[8] Workers care about the monetary return of a job w_n as well as on a non-monetary component $v(n)$ that captures preferences for the types of tasks on the job.

$$u(w_n, n) = w_n + v[n]$$

A job that requires performing reading tasks is such $n = 0$, and we assume that jobs in this economy involve either numeric tasks ($n = 1$, as we show below, a salesperson) or reading tasks ($n = 0$, as we discuss below, personal care worker). We make two extra assumptions. The first is that there is a market return to ability, above and beyond schooling or other covariates, or that $w_n = C_n * w$ where C_n is the numeric ability of the worker and w is the market price of the unit of skill, be it numeric or reading-related. Sorting implies that workers choose the numeracy-intensive job if $u(w_n, n) > u(w_l, 0)$ or

$$wC_n * +v[n] > \quad wC_l + v[0] \quad or \qquad wC_n - wC_l > v[n] - v[0]$$

In other words, a worker will choose a numeracy job when the wage return to his numerical ability -relative to the literacy one- exceeds any possible utility loss from conducting numeric, rather than literacy tasks.

Further using Model (2) $C_n = \alpha_2 n + \varepsilon_n$ and $C_l = \varepsilon_l$,

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[8] Villanueva (2007) shows that workers are willing to sacrifice up to 6% of their wage to work in a job requiring skills that suits their abilities, suggesting that the skill content of a job may enter their utility function.

Now consider the distribution of the observed cross-sectional difference between numeracy and literacy skills in the economy -conditional on the job chosen. Conditional on choosing a numeric job, that gap is:

$$E(\, C_n - C_l | n = 1) = \alpha_2 n + E\left(\varepsilon_n - \varepsilon_l \middle| C_n - C_l > \frac{v[n] - v[0]}{w}\right)$$
$$= \alpha_2 n + E\left(\varepsilon_n - \varepsilon_l \middle| \varepsilon_n - \varepsilon_l > \frac{v[n] - v[0]}{w}\right)$$

That is, the gap between measured numeracy and literacy skills may arise either because workers acquire numeracy skills in their jobs by performing relatively more numeric tasks (whose return we call $\alpha_2 n$) or because of a sorting that arises both from initial comparative advantage in numeracy skills and for taste for jobs that involve numeracy tasks. Separating the sorting and the productivity component is very difficult.

Our strategy to identify α_2 exploits the heterogeneity in the degree of task sophistication that allows us to identify a group of the population for which all the difference between measured numeracy and literacy skills is due to selection. Consider for a second the case of workers with a college degree. Those workers may end up with different numeracy skill levels -relative to their reading one- due to their initial preferences or their choice of major but not, we assume, because their jobs have involved differential basic tasks, like using a calculator or elaborating a budget. We assume that for workers with high education levels, performing simple tasks on their jobs does not lead to an increase in their numerical scores –i.e., for those tasks α_2 equals zero.

Assumption 2: Performing simple numeric tasks at the job does not have a causal effect on the difference between numeracy and literacy skills for workers with a college or high school degree.

Within the group of workers with a college degree, the presence of simple numeric tasks may still be statistically associated to gaps between the numeracy and literacy skills because of sorting. Jobs that involve using a calculator are more likely to have math-related content than jobs that do not, so the correlation between the numeracy vs reading scores and the presence of "simple" numeracy tasks captures preferences towards jobs with numeracy content among workers with a high-school or a college degree. In other words, the difference between numeracy vs literacy skills of workers with either a high-school or a college degree that is associated to conducting simple numeracy tasks (relative to simple reading tasks) provides information about the extent of sorting in occupational choices, or

$$E(\, C_n - C_l | n_s = 1, college) = E\left(\varepsilon_n - \varepsilon_l \middle| \varepsilon_n - \varepsilon_l > \frac{v[n] - v[0]}{w}, college\right)$$

where $n_s = 1$ indicates that the job involves conducting a simple numeracy task. So our strategy is the following. We first estimate for basic school workers a regression of the difference between the (normalized) numeracy vs literacy score on the presence of simple numeric tasks - relative to reading tasks. That estimate measures both the causal impact of performing numeric tasks on the normalized numeracy score plus a sorting component. The second step is to estimate the same regression for a sample of individuals with either a high school or a college degree. Under our assumptions, the coefficient of simple tasks in that sample reflects sorting. Finally, we subtract the sorting component from the estimates in the first step.

In other words, for workers with basic schooling, we estimate an OLS estimate of a regression of $C_n - C_l$ on $(n - l)$, that yields:

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

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, t $\alpha_2 = 0$, so an OLS regression of $C_n - C_l$ on $(J_n - J_l)$ is:

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

So $\hat{a}_{2,basic} - \hat{a}_{2,high\,school}$ is a consistent estimate of the parameter α_2.

One can view our strategy as a difference-in-difference strategy where the treatment is the presence of tasks on the job and the control group are workers with a college or high school degree.

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 that $\alpha_2 = 0$ is not realistic if the tasks considered are complex ones, as those may help any worker to build human capital. Hence, when estimating Model (3) we control for the presence of advanced tasks on-the-job. Secondly, *n-l* is a continuous variable, so the selection component may well be non-linear. Experimenting with non-linear terms in *n* would be interesting, but would also complicate the analysis. Thirdly, one can raise the objection that workers with a college or high school degree may different preferences and ability to sort across jobs than workers with basic schooling. While this can be true, the evidence available about workers with low levels of schooling is that their ability to sort is rather limited. Charles et al. (2016) document that the employment chances of low-educated workers are tied to local industry shocks, as probably they are unlikely to move. Their findings mean that our approach of inferring selection ability from that of workers with higher levels of schooling, if anything, overstates the role of selection. Furthermore, in what follows, we run model (3) for increasingly younger workers, who have had less and less ability to sort over their life-cycle.

Finally, we are taking schooling as exogenous. It is not clear whether the endogeneity of schooling is related to the differential task content of jobs. To informally assess if the endogeneity of schooling affects our estimates, we examine the correlation between performing simple tasks on the job and the difference between numeracy vs literacy scores at various levels of education. To the extent that the correlation does not vary across education groups, other than workers with basic schooling, it gives us confidence that endogeneity of schooling is not affecting our estimates.

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 common issue in the analysis of the variation of skills is the separation of cohort and age effects (Green and Riddell, 2013). Test scores are typically lower among aged individuals, but it is not clear 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, we relate *relative* performance in the numeracy vs the literacy test to the relative intensity in performing numeracy tasks 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- labour market human capital C_0 or between skills ε_m and the skill content of a job

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

Indeed, as Table 2 suggests, a non-negligible fraction of college workers in the countries we consider conduct basic numeracy or literacy tasks on their jobs. It is not clear how such potential mismatch affects our estimates. Firstly, our focus lies on workers with basic schooling, who are unlikely to be in 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

[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 $[n - l]$ 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.

can only aim to recover the average effect of on-the-job learning on skills, leaving an analysis of heterogeneous impacts to future work.

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 internationally comparable data on literacy and numeracy proficiency, as well as on the tasks performed at work by adults aged 16-65 in 24 countries or sub-national entities. We mainly use thirteen countries: Czech Republic, Spain, Estonia, Finland, France, Ireland, Italy, Korea, the combination of England and Northern Ireland (UK, for short), Netherlands, Norway, the Slovak Republic and Sweden. Those are the countries with the largest samples and with detailed information about the number of years of working experience and age. Within those countries, Spain, Estonia, Italy, Netherlands, Norway, UK and Sweden have a sizable fraction of workers with basic schooling. Hence, in those cases we can also conduct country-specific regressions.

In each country a representative sample of adults 16-65 years old took a direct assessment of their proficiency in literacy and numeracy. The survey was implemented either by computer or on paper and pencil[10]. The assessment also tested proficiency in problem solving in technology-rich environments, but we only use literacy and numeracy, as the former was not administered in all countries in our study. For example, Spain did not conduct the problem solving technology assessment, and it is the country that, together with Italy, contains the largest share of respondents with basic schooling. [11] [12]

In addition, PIAAC contains 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 measures of the numeracy and reading task content of jobs.

Experience. In particular, work experience is constructed with 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"*

Tasks. The survey asks each employed respondent about how many times he or she conducted a particular task during the last month. In addition, non-employed respondents with previous labour market experience are also asked about the tasks done in their last job. The number of tasks listed in the survey is large, and we have classified them as either numeracy- or literacy-related. Numeracy-related tasks include elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams, elaborating graphs or using algebra. Literacy-

[10] We control for a dummy that indicates whether the individuals conducted the exam on paper.
[11] Details about the definition of each domain are given by OECD (2013).
[12] All specifications combine of the ten different imputations available for the numeracy or reading score for each test for each individual. In addition, the standard errors in all regressions are corrected for the presence of multiple imputation, along the lines suggested by OECD (2013). To avoid issues about heteroscedasticity, we do not weight the regressions.

related tasks are 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 forms of Vocational Training 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 those forms of Vocational that ISCED considers equivalent to college.

Sample selection. To obtain a large sample of individuals from different countries we pool employed and unemployed individuals as well as females and males between 16 and 55 years of age. We decided to stop at 55 because of the incidence of retirement in our sample. At age 55, in some of the countries we analyze, the fraction of retired workers jumps to 30%. As there is evidence pointing at retirement as being associated to a sharp cognitive decline and we focus on workers in the labor force, we chose that age range. We also censored experience levels higher than the difference between age and the sum of six plus the number of years of education. Finally, we exclude from the sample those workers who have not had any labour market experience.

Summary statistics: experience and tasks

Table 1 shows summary statistics for the baseline sample of prime-aged individuals (aged 16-55). 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 Italy (47%) and lowest in the Czech Republic (6%). The average number of years worked does not change much across countries, in contrast.

Table 2 shows to what extent workers perform different tasks on their job. As discussed in Section 2, we distinguish between simple and advanced tasks, as their impact on human capital accumulation is 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[13]. 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.

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

[13] 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.

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 countries. Finally, excluding Finland and the Czech and Slovak Republics between one quarter and one third of individuals with basic schooling perform at least one of the simplest tasks. That similarity may be surprising, given the large cross-country differences 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 graduates in the Czech and Slovak Republics or in Norway, Sweden, Netherlands or Estonia conduct at least one advanced task in their job while the same 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 (not shown). Conversely, among individuals with high educational levels, the most common advanced tasks are preparing graphs and reading books or academic journals.

Thus, the statistics in Table 2 suggest that, in most 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.

4. Work experience and cognitive skills

Table 3 motivates the analysis by examining how numeracy skills vary with years of experience. Namely, we pool males and females and run country-specific regressions of the (normalized) numeracy score in PIAAC on a second-order polynomial of years of working experience minus 15, interacted with dummies denoting the level of schooling attained. We pool males and females. Also, for the purposes of Table 3, we only use eight economies where the fraction of respondents with compulsory schooling is large enough to conduct country-specific analysis (Estonia, Spain, Italy, United Kingdom, Ireland, the Netherlands, Norway and Sweden). In addition, to make years of labour market experience comparable between college graduates and respondents with basic schooling, we focus on a sample where all respondents are likely to have finished their studies, and use a sample of 26-45 year olds[14].

The coefficient of experience can then be interpreted as the percent standard deviation change in the numeracy score when experience increases by one year for a worker. We use the group of workers with basic schooling and 15 years of working experience as the reference group. 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[15].

Regardless the country of residence and among respondents with basic schooling, one year of labour market experience is associated with a statistically significant increase in the score in

[14] We only do this in Tables 3 and 3B to motivate the analysis. In the rest of the paper, we include workers between 16 and 45 years of age, as we are interested in the first years of experience of respondents with compulsory schooling only.

[15] In particular, we include dummies for foreign-born, married, health status, attitudes towards learning and dummies of age in 5-year bands.

the numeracy test. For example, a Spanish worker with basic schooling and 16 years of experience scores 1.7 percent of one standard deviation (=0.017 in Table 3, row 1, column 2) higher than a similarly schooled worker with 15 years of working experience. The same increase of 1 year of labour market experience results in an increase of 3.5 percent of one standard deviation in the numeracy score in Norway. For the rest of the countries considered, one extra year of labour market experience is also positively associated with the numeracy score of respondents with basic schooling and 15 years of experience, and the increase in the numeracy score lies between 1.7 percent and 3.5 percent of one standard deviation.

Conversely, for university graduates the correlation between years of working experience and standardized scores in the numeracy test is weaker. The interaction between years of experience (actually, its deviation from 15) and the dummy for college graduate is presented in row 3 of Table 3 and it is negative and statistically different from zero at the 95% confidence level in all countries considered. For example, a Swedish college graduate with 16 years of experience in the labour market obtains a math score that is only 0.2 percent of one standard deviation higher than a college graduate with 15 years of experience (0.002 is obtained by adding the estimate of -0.021 in row 3, column 8 of Table 3 to the 0.023 estimate in row 1, column 8). For a respondent with basic schooling, the corresponding estimate is 2.3 percent of one standard deviation, an estimate about an order of magnitude larger. The impact of one extra year of labour market experience on the numeracy score of college graduates is somewhat larger in England/Northern Ireland than in Sweden. A British college graduate with 16 years of experience has about 0.9 percent of one standard deviations higher score than a similar graduate with 15 years of experience (0.9=0.022-0.013, adding up the estimates in row 3, column 4 of Table 3 and in row 1, column 4 if Table 3). However, the estimated impact is modest compared to the return of 2 percent of one standard deviations increase for one year of experience for a British respondent with *basic* schooling.

Figure 1 illustrates the countr-specific profiles. 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.

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 and, to avoid heterogeneity in the skills returns across gender, we focus on males only. The advantage of that specification is that we can capture more accurately the concavity of the effect of labour market experience on standardized numerical test scores while at the same time holding constant the covariates listed at the bottom of Table 3[16]. 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 quantitative estimates of the impact of experience on numeracy scores vary across

[16] Namely, we pose a flexible relationship between numeracy scores and experience, while controlling for a linear index of the covariates at the bottom of Table 3. 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).

specifications –for example, one can compares the skill returns to experience in row 5 of Table 3 to the first row with estimates in Table 3B. However, both methods deliver qualitatively similar results. In all countries but in Estonia the link between the first year of labour market experience and the numeracy score is strongest for individuals with basic schooling at low levels of working experience, as can be seen by comparing the estimates in the first row of Table 3B to the rest of the estimates. Moreover, among respondents with compulsory schooling, the skill return to one extra year of labour market 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). On the other hand, the link between the number of years of working experience and average numeracy scores among respondents with a college degree is statistically significant at the beginning of the career only in England/Northern Ireland and in Norway. After 5 or 10 years the skill return to one extra year of labour market experience is basically zero in all countries considered.

Summarizing, the evidence shown in Tables 3 and 3B is consistent with the notion that formal education and labour market experience are substitutes in the accumulation of cognitive skills. 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. 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, the available evidence suggests that numeracy scores correlate with wages at all points of the distribution of skills (see Hanushek et al., 2015), indicating that “ceiling effects” may not be that strong.

Secondly, the patterns in Tables 3 and 3B suggest that it is in the early years in the labour market where labour market experience increases most the numeracy scores of respondents with compulsory schooling. Hence, in the rest of the paper, we present estimates for the full 16-55 age range, but focus specially on samples of respondents aged 16-45 or even younger.

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

5. Job tasks and cognitive skills

As discussed in Section 2, the estimates in Table 3 may be affected by omitted variable biases, because the unobserved initial endowment of human capital is likely to be correlated with years of working experience. In this Section, we regress the relative performance in numeracy vs reading tests on the relative specialization in numeracy tasks on the job, a specification implicitly controls for the initial endowment of human capital.

This simple idea relies on two assumptions. The first is that the numeracy and the reading 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 reading tasks. 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. 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 at least once a month she elaborates a budget, reads a diagram, uses a calculator, and computes a fraction 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 0.25=(1/4). For example 15% of low educated workers in the overall sample are granted 1. We define “Basic literacy tasks” in a similar fashion. The degree of specialization is defined as the difference between “Basic math tasks” and “Basic literacy tasks”.

A second manner of computing tasks on the job takes into account the frequency with which tasks are performed. Individuals in PIAAC are asked to report whether they perform the task each day, at least once a week, at least once a month or never. Thus, this measure takes into account the “fraction of time” that a worker reports devoting to a particular task. That is, we assign a worker who reports performing one particular task every day an intensity of 100%. A worker who conducts the task at least once a week an intensity of 50% and a worker who conducts the task at least once a month an intensity of 20%. We then combine the tasks as we did in the previous measure.

An illustration: Task specialization by occupation and industry

We illustrate the different degrees of numeracy specialization by aggregating skills at the occupation level. Table A1 of the Appendix shows the different task intensity of industries that employ low-educated individuals. Examples of the main tasks conducted on-the-job are also provided in that Table –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 7% of all individuals with basic schooling in the full sample. Workers in that occupation are comparatively specialized in reading task, as the frequency-adjusted difference between their numerical vs reading tasks is negative (-0.185 in the second Column of Table A1). 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.

At the opposite extreme of the spectrum are *sales workers* (occupation number 52) an occupation that employs 7% of all individuals with basic schooling in the full sample. Those workers specialize in numerical tasks. Namely, the frequency-adjusted difference between intensity in numerical and reading tasks is positive, 0.086 (or devote 8.6% more of their time to numerical tasks than to reading ones).

Note that both occupations may employ workers with different **levels** of numeracy or literacy skills –sale workers may score similarly in 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 2 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 with compulsory schooling 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 (see Figure 3). 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 4 implements a version of Model (3) on the full sample of countries.[17] We pool observations 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 55 years of age) and do not distinguish between simple and advanced tasks.

The coefficient of $task_{num} - task_{lit}$ in the first row, first column of Table 4 is 0.168, implying that, relative to workers whose jobs have a similar incidence of numeric and literacy tasks, workers with basic schooling in jobs that fully specialize in numerical tasks perform 16.8% of one standard deviation better in the numeracy test than in the reading test. The impact of full specialization in numeric tasks among workers with a high school degree is obtained by adding the estimate in column 1 row 2 of Table 4 to that in column 1, row 1, and amounts to 12.6%=(0.168-0.042) of one standard deviation –about one quarter smaller that the estimate for workers with basic schooling. The impact of full specialization in numeric tasks for workers

[17] We have experimented conducting country-specific regressions, at least for those countries in Table 3 where there is enough sample to estimate models on respondents with compulsory schooling. Results available upon request suggest that, aside from Spain and Ireland, the estimates are generally in line with those we show below.

with a college degree is identical to that of workers with a high school degree. The results are virtually unchanged when we introduce 56 dummies indicating the current or last 2-digit occupation of the respondent or 21 industry dummies (columns 2-3 in Table 4).

To get a grasp of the magnitude of the impacts, consider the difference between the specialization in numeracy tasks of sales workers vs personal care workers. According to the frequency-unadjusted measure of specialization, the difference in specialization in numeracy tasks between both groups is about 32%, or about 2 extra numerical tasks. The estimate implies that conducting those 2 extra numerical tasks increases the score in the numeracy test (relative to the literacy test) by 0.168*0.33=5.5% of one standard deviation.

Heterogeneity by age-cohort 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. On the other hand, the strong changes in the occupational structure across cohorts may have affected the set of learning possibilities faced by younger cohorts. Hence, we look at the sample of respondents below 45 years of age in 2012. The link between specialization in numerical tasks and the relative score in the numerical test is slightly larger for younger workers with basic schooling: full specialization in numeracy tasks increases the relative numeracy score by 17% of one standard deviation in the full 16-65 sample and by 20% of one standard deviation in the 16-45 sample. However, according to the estimates in Table 4, column 6, full specialization in numerical tasks increases the relative numeracy scores of respondents with a high school degree by 12% of one standard deviation (=0.192-0.073, in column 6, row 2 of Table 4). Full specialization in numerical tasks in the prime age sample also increases the relative score in the numeracy test by a similar 12% of one standard deviation (=0.192-0.07) among respondents with a college degree.[18]

Adjusting by task intensity.

The results in Table 4 do not distinguish if a task is conducted at least once a month or every day, so to examine the robustness of the results we construct a new measure of task intensity that explicitly takes into account the report of the worker about the frequency with which tasks are performed. In this case, full specialization in numerical tasks implies that the worker performs all numerical tasks considered every day in his or her job.

The results shown in Table 5, row 1, column 1 indicate that respondents who fully specialize in numerical tasks by conducting *all* numerical tasks on their jobs *every day* score 22% of one percent of one standard deviation higher in the numeracy than in the reading score (Table 5, row 1, column 1). However, when we use that alternative measure, the link between specialization in numerical tasks and the relative performance in the numeracy vs the reading test is 18% of one standard deviation, only slightly lower among respondents with a high school

[18] Those results suggest that the possible skill deterioration documented in previous papers could be explained by differences in the type of tasks conducted on the job over the life cycle, a topic we do not explore here.

degree (19% of one standard deviation). We discuss the result in detail below, when we distinguish between specializations in advanced vs basic tasks.

We explore now the link between specialization in numerical tasks and relative performance in numeracy tests across different age groups. The impact of full specialization in numerical tasks is largest among the youngest cohorts. For example, considering the group of respondents with basic schooling and between 16 and 35 years of age, full specialization in numerical tasks increases the numeracy score by 36% of one standard deviation (Table 5, column 7, row 1). The magnitude of the impact of specialization is reduced to a half among workers with a high school or a college degree. Namely, for individuals with a high school degree, full specialization in numerical tasks leads to a 18% of one standard deviation (=0.356-0.172, Table 5, column 7, rows 1 and 2) while the estimate is 20% for college graduates (=0.356-0.152, Table 5, column 7, rows 1 and 3).

Overall, the results in Table 5 are again consistent with the notion that conducting particular tasks on the job increases the skills of workers with basic schooling, and that the effect is strongest for youngest cohorts, who are accumulating their first years of experience. The results are weaker among respondents with either a high school or a college degree. The result points again at formal schooling and practice on the job being substitutes –a surprising finding, as one could well expect that the performance of tasks on the job reinforces pre-labour market differences associated to differences in formal schooling.

6. Simple vs advanced tasks: the role of sorting

The estimates in Tables 4 and 5 reflect workers' sorting across jobs according to their initial endowment of skills. As discussed in Section 2, we infer the extent of sorting 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 relative scores must reflect sorting across jobs –or reverse causality that runs from initial proficiency in numeracy vs reading to specializing in numeric tasks on the job.

6.1. Task specialization measures unadjusted by frequency

The estimates in the first row, first column of Table 6 imply that respondents with basic schooling who fully specialize in *basic* numerical tasks on their jobs score 9 percent of one standard deviation higher in numeracy –compared to workers who are equally specialized in numeric and reading 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. On the other hand, the link between conducting advanced tasks on the job and the relative performance in the numerical test, shown in row 4 of Table 7 is weak. The data does not allow us to disentangle if that weak result arises from measurement error –basic school workers do not really perform those tasks- or because formal schooling does complement sophisticated tasks.

As in the previous Tables, we find that the link between specialization in performing basic numerical tasks (vs reading ones) and the relative performance in the numeracy test is strongest among the youngest cohorts. Columns 4-6 in Table 6 focus on respondents between 16 and 45 years of age, while Columns 7-9 use a sample between 16-35 years. Among respondents with basic schooling, conducting all numerical tasks considered leads to an increase in the relative numeracy score of 12% of one standard deviation (row 1 and columns 4-9 of Table 6).

The degree of sorting: As mentioned above, we can recover an estimate of the degree of sorting between initial endowment and numeracy-intensive jobs by examining at groups with higher schooling levels (with either a high school or a college degree). In practice, we subtract the estimate in either row 2 or 3 from that in row 1 in Table 6, yielding the impact of specialization in basic numeracy tasks on the relative performance in the numeracy test for those groups. The estimate is remarkably stable across cohorts. For college graduates in the full 16-55 sample, full specialization in basic numeracy tasks increases the score by 6% of one standard deviation (=0.092-0.0329 subtracting the estimate in row 3 from that in row 1 in the first column of Table 6). Turning to college graduates in the 16-45 sample, the estimate is again 6.2% of one standard deviation (0.062=0.138-0.076, subtracting the estimate in row 3 from that in row 1 in Column 4 of Table 6) and it is about 4.2% in the 16-35 sample (0.042=0.141-0.099, subtracting the estimate in row 3 from that in row 1 in Column 7 of Table 6). The estimates of the degree of sorting are similar when we use respondents with a high school degree. The estimates of sorting lie between 8% of one standard deviation in the full sample (0.08=0.092-0.013, subtracting the estimate in row 2 from that in row 1 in the first column of Table 6) and 7% of one standard deviation (0.07=0.141-0.071, subtracting the estimate in row 2 from that in row 1 in the seventh column of Table 6).

The magnitude of the impact of task specialization on human capital measures in Table 6.

We discuss now our estimates of the impact of conducting tasks on the job on the relative numeracy score as implied by the results Table 6. In the overall 16-55 sample, the estimate of full specialization in numerical tasks on relative performance in the numeracy test is 9.2% (column 1, row 1 in Table 6). As mentioned above, the corresponding estimate among respondents with a college degree is 6% (column 1, subtracting row 3 from row 1 in Table 6), leaving a causal estimate of full specialization of 3.2% (0.032=0.092-0.06) of one standard deviation (standard error=2%). This estimate is relatively small and imprecise.

The estimates become larger when we focus on the 16-45 age cohort. In that case, the estimate of full specialization on the relative performance in the numeracy test among basic schooling respondents is 13.8% of one standard deviation (shown in the first row of column 4 in Table 6). Subtracting the 6.2% impact among respondents with a college degree (0.062=0.138-0.076) leaves an estimate of 7.6% of one standard deviation (standard error: 3.1%). The estimate is similar when we look at the 16-35 age cohort, and increases to 9.9% of one standard deviation (obtained by subtracting from 14.1% in row 1 of column 7 the estimate among college grads, which is 0.042=0.141-0.099). In sum, full specialization in numerical tasks increases the relative score in the numerical test by between 3.2% and 9.9% of one standard deviation.

As mentioned in Section 4, in what follows we focus on the estimate for the 16-45 cohort for two reasons. The first is that the youngest cohorts have had less time to sort in the labour market, so estimates in that subsample are most likely to reflect the causal impact of task specialization on measures of human capital. The second reason is that the analysis was motivated by the strong correlation between experience and human capital measures for youngest cohorts. As documented in Tables 3 and 3.B, the impact of experience on human capital is much lower among cohorts older than 45.

6.2. Adjusting by the frequency of tasks

Table 7 shows a new set of estimates using the alternative measure of specialization that adjusts for the frequency of tasks on the job. As in the previous case, a respondent with basic schooling who performs *everyday all the basic* numerical tasks we consider performs between 13% and 26% of one standard deviation better in the numerical test than in the reading one –compared to a worker who does not specialize. The 13% estimate is obtained in a sample that includes individuals aged 16-55, while the impact of 26% is estimated in the sample of respondents who were between 16-35 years of age in 2011-2012.

On the other hand, the estimates of the degree of sorting are again constant across the different cohorts, and indicate that respondents with a high school or college degree who fully specialize in basic tasks perform about 10% of one standard deviation better in the numeracy test than in the reading test –compared to a similar worker who does not specialize. For example, in Column 1 of Table 7, one can subtract the estimate in row 3 from that in row 1, obtaining 10% (0.10=0.13-0.02). The corresponding estimate in Column 4 (the 16-45 cohort) is 11% (0.115=0.207-0.092) while that in Column 7 is again 10.5% (0.105=0.261-0.156).

The magnitude of (frequency-adjusted) task specialization on human capital

When we proceed in the same manner as in Section 6.1, we find that the estimate of (frequency-adjusted) specialization on numerical tasks on the relative performance in the numeracy test among basic schooling respondents is 20% of one standard deviation (shown in the first row of column 4 of Table 7). Subtracting the 11% impact among respondents with a college degree (0.11=0.207-0.96) leaves an estimate of 9.6% of one standard deviation (standard error: 3.6%). The estimate corrected by sorting in the 16-35 age cohort is 15% of one standard deviation (standard error: 5%). Using respondents with high school degree to control for sorting leads to very similar estimates.

7. Assessing the magnitude of the estimates

Overall, the results are consistent with the hypothesis that on-the-job learning may substitute formal schooling for YOUNG 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.

Our estimates suggest that specializing in numeracy tasks increases the differential numerical score of individuals with basic education by about 13.8 percent of one standard deviation (table 6, row 1 column 4). If we further assume that there are selection effects that can be identified by the impact of specialization on numeracy scores among college graduates, the corresponding estimate would be 7.6 percent of one standard deviation, as described in Section 6.1.

We do not have information on all tasks performed in all jobs during the working history of a worker, so we cannot establish if workers conducted numerical or literacy task in their current job only or during their whole working lives. Hence, we make the rather conservative assumption that workers conducted numerical or literacy tasks during 12 years of experience (the sample average, shown in Table 1). That conservative assumption implies that one year of experience increases numeracy skills by between 0.67% and 1.8% of one standard deviation.

Hanushek et al. (2015) estimate that increasing compulsory education by one year 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 1.5 = (2.7/1.8) and 4.3 years (=2.9/0.67) of on-the-job learning.

8. Conclusions

Numeracy skills account for a substantial share of the variation in labour 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 on individuals with low levels of schooling. The results, suggest that in all countries considered labour market experience is associated with an increase in cognitive skills at the beginning of the working life especially in the case of workers with low levels of education.

We dig into the possible channels behind these results. In particular we control for individual fixed effects by analyzing how the relative performance in numeracy versus literacy varies with the differential exposure to numeracy versus literacy tasks on-the-job, we find that, among individuals with at most compulsory schooling, full specialization in basic numerical tasks increases the relative numeracy score by between 7.6 and 11.8 percent of one standard deviation. Our results are consistent with the notion that formal schooling and on-the-job learning are substitute inputs in human capital production for workers with low levels of education.

Our findings have some implications for the design of active labour 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 educated 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, the amount of on-the-job learning is determined by jobs requirements, which vary greatly across sectors.

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Table 1: Summary statistics

Summary Statistics		CZECH REP.	ESTONIA	SPAIN	UNITED KINGDOM (c)	FINLAND	FRANCE	ITALY	IRELAND	KOREA	NETHERLANDS	NORWAY	SLOVAK REP.	SWEDEN
Numeracy test (mean)	Basic	236	239	228	222	251	169	228	218	228	247	245	221	239
	High school	272	269	256	261	282	239	264	253	259	284	275	278	278
	College	312	293	281	288	318	295	283	285	285	311	308	306	312
Reading test (mean)	Basic	244	247	234	238	257	191	233	232	241	253	253	232	244
	High schol	270	271	260	273	289	251	263	265	268	289	274	275	279
	College	304	294	285	297	323	295	284	292	291	314	305	296	311
Working experience (mean)		16.0	15.3	14.6	16.2	15.1	15.22	15.2	15.12	12.2	16.4	16.1	14.8	15.7
Fraction of males		52.0	49.0	51.1	50.0	51.0	50.0	50.5	48.0	50.5	50.74	52.0	51.0	50.75
Fraction with basic schooling		6.0	13.0	43.0	21.0	10.0	3.0	47.0	22.0	10.0	25.0	20.0	14.0	13.0
Fraction with high school		73.0	46.0	22.0	40.0	62.0	60.0	39.0	41.0	44.0	40.0	40.0	64.0	55.0
Fraction with a college degree		20.0	40.0	34.0	39.0	28.0	96.0	14.0	37.0	45.0	34.0	40.0	22.0	32.0
Sample size		3620	5034	4265	6441	3313	4607	3214	4322	4522	3361	3311	3837	2801

Source: PIAAC.

Footnotes:

a. Respondents between 16 and 55 years of age

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.

c. In all Tables we use "United Kingdom" to refer to the pooling of the data of England and Northern Ireland, as provided by PIAAC data producers

d. Descriptives consider PIAAC weights. Numeracy and literacy scores are the average of the 10 possible values provided by PIAAC

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

Level of education	CZECH REP.	ESTONIA	SPAIN	UNITED KINGDOM	FINLAND	FRANCE	ITALY	IRELAND	KOREA	NETHERLANDS	NORWAY	SLOVAK REP.	SWEDEN
						Basic numeracy tasks							
Basic school	4.6	27.5	29.0	28.9	11.2	25.4	34.6	26.2	36.4	31.8	38.5	11.8	35.1
High school	7.3	25.2	32.8	36.7	9.2	36.5	32.1	36.4	36.4	19.5	36.6	22.6	38.2
College	4.5	14.2	20.2	20.6	4.3	21.0	20.1	22.5	21.0	38.5	17.8	7.0	22.8
						Advanced numeracy tasks							
Basic school	47.8	28.1	12.6	18.2	49.3	5.2	7.7	11.9	18.0	22.0	25.5	8.5	25.5
High school	71.4	51.3	30.7	38.8	75.5	25.0	30.5	25.4	35.0	46.8	46.0	47.2	41.4
College	87.1	75.7	60.1	66.7	91.9	66.6	58.9	60.7	59.6	71.6	75.2	81.6	71.1

Level of education	CZECH REP.	ESTONIA	SPAIN	UNITED KINGDOM	FINLAND	FRANCE	ITALY	IRELAND	KOREA	NETHERLANDS	NORWAY	SLOVAK REP.	SWEDEN
						Basic reading tasks							
Basic	41.9	36.1	34.6	35.3	24.2	24.2	28.5	29.2	27.9	38.4	21.2	20.5	27.0
High school	29.0	31.8	20.0	31.9	13.8	33.4	28.0	34.0	23.3	28.5	17.4	36.9	23.8
College	7.4	11.5	27.0	16.0	3.9	17.1	13.7	17.4	8.6	9.0	5.3	10.8	6.8
						Advanced reading tasks							
Basic	15.3	25.6	17.7	25.8	44.0	16.6	17.6	19.7	27.7	33.4	55.1	6.2	44.0
High school	51.6	49.0	38.1	51.9	74.0	39.9	42.3	35.5	49.7	60.9	74.6	38.3	64.8
College	84.9	82.0	65.8	75.9	93.2	74.5	74.8	72.1	75.0	86.9	91.3	79.7	90.4

Source: PIAAC

a. Sample of respondents16 to 55 years of age 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 reading tasks: reading email, reading guides, reading manuals, writing emails, writing reports, reading articles

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

c. Descriptives consider PIAAC weights. United Kingdom denotes England and Northern Ireland.

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

Parametric analysis	ESTONIA	SPAIN	ITALY	UNITED KINGDOM	IRELAND	NETHERLANDS	NORWAY	SWEDEN
1. Working experience - 15	0.030***	0.017***	0.029***	0.022***	0.029***	0.019**	0.035***	0.023***
	(0.008)	(0.004)	(0.005)	(0.004)	(0.006)	(0.008)	(0.008)	(0.009)
2. (Working experience - 15)*High school	-0.009	-0.0046	0.0014	-0.001	-0.012	-0.012	-0.015*	-0.001
	(0.008)	(0.0067)	(0.006)	(0.005)	(0.007)	(0.009)	(0.009)	(0.009)
3. (Working experience - 15)*College	-0.016*	-0.013**	-0.020**	-0.013**	-0.019***	-0.032***	-0.028***	-0.021**
	(0.008)	(0.005)	(0.009)	(0.005)	(0.007)	(0.009)	(0.009)	(0.009)
4. (Working experience - 15)^2	-0.0016***	-0.0011***	-0.0013***	-0.0009***	-0.0009***	-0.0014***	-0.0007**	-0.002***
	(0.0004)	(0.0121)	(0.0003)	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
5. Impact of one year of experience at entry	0.078	0.050	0.068	0.049	0.056	0.061	0.056	0.083
6. Impact of one year of experience at entry, colle	0.062	0.037	0.048	0.036	0.037	0.047	0.028	0.062
Obs.	2,921	2,612	2,612	3,859	2,612	1,830	1,924	1,590
R2	0.252	0.401	0.401	0.372	0.401	0.386	0.434	0.516

Source: PIAAC selected sample (Spain, Italy, Ireland, UK -England and Northern Ireland-, Sweden, Norway, Estonia and the Netherlands, where the sample of respondents with basic schooling is large enough)
Footnotes:
a. The sample contains respondents 26 to 45 years old. The dependent variable is the normalized numeracy score (i.e, the score divided by the standard deviation of respondents between 26 and 45 years of age)
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	ES	SPAIN	ITALY	UK	IRELAND	NO	NL	SW
Basic schooling	**0**	0.007	0.158***	0.063*	0.096***	0.113***	0.128***	n.a.	n.a.
		(0.026)	(0.027)	(0.035)	(0.022)	(0.032)	(0.033)		
	10	0.029	0.054***	-0.003	0.076***	0.077***	0.083***	n.a.	n.a.
		(0.018)	(0.017)	(0.019)	(0.014)	(0.0225)	(0.020)		
	15	0.066**	0.017**	0.009	0.021*	0.054***	0.051***	n.a.	n.a.
		(0.029)	(0.008)	(0.014)	(0.011)	(0.017)	(0.014)		
Obs.		201	530	288	306	199	136		
High School	**0**	0.020	0.060	0.047	0.030	0.018	0.087*	n.a.	0.071
		(0.025)	(0.042)	(0.031)	(0.053)	(0.033)	(0.049)		(0.043)
	10	0.012	0.012	0.045***	0.048***	0.036***	0.025	n.a.	0.028***
		(0.011)	(0.015)	-0.014	-0.017	(0.012)	(0.020)		(0.11)
	15	-0.000	0.018	0.021*	0.021**	0.030***	0.137	n.a.	0.029***
		(0.009)	(0.013)	(0.11)	(0.103)	(0.010)	(0.135)		(0.008)
Obs.		678	261	485	523	492	393		417
College	**0**	0.062	0.028	0.018	0.093***	-0.009	0.112**	0.003	0.047
		(0.047)	(0.048)	(0.059)	(0.024)	(0.027)	(0.048)	(0.040)	(0.050)
	10	0.016	0.002	0.014	0.016*	0.018*	0.017	-0.025*	0.020
		(0.016)	-0.009	(0.021)	(0.0085)	(0.009)	(0.122)	(0.015)	(0.130)
	15	-0.025*	-0.0048	-0.023	-0.003	0.003	-0.003	-0.015	0.003
		(0.015)	(0.120)	(0.023)	-0.01	-0.009	(0.008)	(0.012)	(0.011)
Obs.		464	452	169	629	551	442	346	332

Source: PIAAC selected sample (Spain, Italy, Ireland, UK -England and Northern Ireland-, Sweden, Norway, Estonia and the Netherlands, where the sample of respondents with basic schooling is large enough)

Footnotes: a. Males 26 to 45 years of age. The dependent variable is the numeracy score (divided by the country-specific standard deviation for males of the age group)

b. The coefficients shown are the impact of an additional year of experience on the normalized 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: The impact of task specialization on relative performance in numeracy and literacy score (All countries pooled)

	Dependent variable: (Normalized math score-Normalized reading score)					
Variables	Sample with respondents between 16-55 years of age			Sample with respondents between 16-45 years of age		
	(1)	(2)	(3)	(4)	(5)	(6)
1. (Numeracy-Literacy tasks)	0.168***	0.170***	0.156***	0.198***	0.202***	0.192***
	(0.017)	(0.0174)	(0.0177)	(0.0212)	(0.0217)	(0.0218)
2. (Numeracy-Literacy tasks)*High school	-0.042***	-0.051***	-0.0527***	-0.0589***	-0.0718***	-0.073***
	(0.017)	(0.0171)	(0.0177)	(0.0212)	(0.0216)	(0.0217)
3. (Numeracy-Literacy tasks)*College	-0.042***	-0.045***	-0.0469***	-0.0637**	-0.0685**	-0.070**
	(0.019)	(0.0198)	(0.0198)	(0.0234)	(0.0238)	(0.0240)
Average number of obs.	50,608	50,608	50,608	35,016	35,016	35,016
Average R2	0.097	0.101	0.075	0.092	0.0935	0.094
Country dummies	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
2-digit occupation dummies	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES

Source: PIAAC full sample -see Table 1

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.

"Numeracy tasks" task is the fraction of all numeracy 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

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.

Each estimate is the average of 10 different regressions. Standard errors are adjusted by multiple imputation and, within each implicate, by heteroscedasticity

***,**,* 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 (taking into account task intensity)

	Dependent variable: (Normalized math score-Normalized reading score)								
Variables	16-55 years of age			16-45 years of age			16-35 years of age		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. (Fraction of time numeracy-Fraction of time Literacy tasks)	0.226***	0.212***	0.199***	0.317***	0.298***	0.289***	0.356***	0.341***	0.338***
	(0.035)	(0.036)	(0.036)	(0.0466)	(0.047)	(0.0473)	(0.0466)	(0.064)	(0.064)
2. (Fraction of time numeracy-Fraction of time Literacy tasks)*High school	-0.036	-0.0273	-0.031	-0.139***	-0.131***	-0.134***	-0.172***	-0.163***	-0.162***
	(0.039)	(0.039)	(0.039)	(0.058)	(0.051)	(0.051)	(0.070)	(0.069)	(0.069)
3. (Fraction of time numeracy-Fraction of time Literacy tasks)*College	0.004	0.0135	0.0102	-0.101**	-0.080	-0.083	-0.152**	-0.128	-0.124*
	(0.039)	(0.0394)	(0.039)	(0.050)	(0.051)	(0.051)	(0.070)	(0.069)	(0.069)
Average number of obs.		50,608			35,016			18,779	
Average R2	0.097	0.101	0.075	0.088	0.093	0.095	0.078	0.083	0.0855
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
2-digit occupation dummies	NO	YES	YES	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES	NO	NO	YES

Source: PIAAC full sample -see Table 1

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 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 time that the respondent reports having performed in his or her job (current or last). Literacy task is the fraction of time when the respondent performs literacy tasks.

The difference between "numeric" and "literacy task" is the degree of specialization in one type of tasks. It takes value 1 if the individual devotes *all* the time to numeric tasks in his or her job .

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.

Each estimate is the average of 10 different regressions. Standard errors are adjusted by multiple imputation and, within each implicate, by heteroscedasticity

***,**,* 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 score-Literacy score)								
	Sample with respondents between 16-55 years of age			Sample with respondents between 16-45 years of age			Sample with respondents between 16-35 years of age		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. (Numeracy-Literacy tasks)$_{basic}$	0.092***	0.077***	0.0694***	0.138***	0.122***	0.116**	0.141***	0.125***	0.124**
	(0.0213)	(0.0215)	(0.0215)	(0.0267)	(0.0267)	(0.0271)	(0.037)	(0.037)	(0.037)
2. (Numeracy-Literacy tasks)$_{basic}$*High school	-0.013	-0.008	-0.012	-0.054*	-0.049	-0.052*	-0.071*	-0.067	-0.069*
	(0.024)	(0.0242)	(0.0242)	(0.030)	(0.030)	(0.030)	(0.041)	(0.041)	(0.041)
3. (Numeracy-Literacy tasks)$_{basic}$*College	-0.0329	-0.0197	-0.0228	-0.076**	-0.0610*	-0.063**	-0.099**	-0.083*	-0.083*
	(0.025)	(0.025)	(0.0257)	(0.031)	(0.0310)	(0.031)	(0.043)	(0.0430)	(0.043)
4. (Numeracy-Literacy tasks)$_{advanced}$	0.0325*	0.0404*	0.0490	0.0320	0.0366	0.032	0.034	0.042	0.034
	(0.0206)	(0.0260)	(0.0328)	(0.0251)	(0.0252)	(0.0252)	(0.034)	(0.034)	(0.034)
5. (Numeracy-Literacy tasks)$_{advanced}$*High school	0.005	0.002	0.00998	0.007	0.008	0.009	0.002	0.002	0.01
	(0.0206)	(0.023)	(0.0374)	(0.027)	(0.0288)	(0.0276)	(0.037)	(0.037)	(0.037)
6. (Numeracy-Literacy tasks)$_{advanced}$*College	0.0539**	0.0478*	0.0466	0.055*	0.0533*	0.0547***	0.062*	0.061*	0.066*
	(0.0228)	(0.0228)	(0.0369)	(0.0277)	(0.0277)	(0.0277)	(0.037)	(0.037)	(0.037)
Obs.		50,608			36,596			18,779	
R2	0.091	0.095	0.098	0.088	0.093	0.095	0.077	0.083	0.085
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Occupation dummies	NO	YES	YES	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES	NO	NO	YES

Source: PIAAC full sample -see Table 1

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

Variables	Dependent variable: (Numeracy score-Literacy score)								
	16-55 years of age			16-45 years of age			16-35 years of age		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{basic}$	0.136***	0.136***	0.117***	0.207***	0.194***	0.189**	0.261***	0.25***	0.253**
	(0.0262)	(0.026)	(0.026)	(0.0329)	(0.033)	(0.033)	(0.045)	(0.045)	(0.045)
2. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{basic}$*High school	-0.015	-0.015	-0.012	-0.092**	-0.087**	-0.091**	-0.155**	-0.151**	-0.156**
	(0.029)	(0.029)	(0.029)	(0.036)	(0.037)	(0.033)	(0.050)	(0.050)	(0.050)
3. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{basic}$*College	-0.020	-0.020	-0.008	-0.096**	-0.078**	-0.083**	-0.156**	-0.149**	-0.140**
	(0.030)	(0.030)	(0.0303)	(0.037)	(0.037)	(0.039)	(0.050)	(0.051)	(0.051)
4. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{advanced}$	0.106*	0.106**	0.109**	0.064	0.0366	0.057	0.054	0.060	0.048
	(0.0406)	(0.0406)	(0.0405)	(0.049)	(0.0252)	(0.049)	(0.065)	(0.065)	(0.055)
5. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{advanced}$*High school	-0.0396	-0.040	-0.0388	-0.004	0.008	0.002	0.028	0.025	0.036
	(0.044)	(0.044)	(0.044)	(0.054)	(0.0288)	(0.053)	(0.061)	(0.070)	(0.072)
6. (Fraction of time in numeracy-Fraction of time in Literacy tasks)$_{advanced}$*College	0.008	0.008	0.004	0.056	0.055	0.0597	0.075	0.072	0.082
	(0.044)	(0.044)	(0.044)	(0.055)	(0.052)	(0.052)	(0.070)	(0.071)	(0.070)
Obs.		50,608			36,596			18,779	
R2	.100	0.103	0.104	0.091	0.093	0.095	0.079	0.085	0.086
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
2-digit occupation dummies	NO	YES	YES	NO	YES	YES	NO	YES	YES
Industry dummies	NO	NO	YES	NO	NO	YES	NO	NO	YES

Source: PIAAC full sample -see Table 1

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 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),

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

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 A1: Frequency of numeracy and literacy tasks (basic schooling)

OCCUPATION (ISCO CLASSIFICATION)	Share of workers (basic schooling)	Fraction time numeric-literacy task	BASIC NUMERACY TASKS				BASIC LITERACY		
			Elaborate budgets	Use calculator	Use fractions	Read diagrams	Read emails	Read guides	Write emails
			(Relative to the average)				(Relative to the average)		
11 Chief executives, senior officials and legislators	0.60	0.020	0.000	1.740	2.104	0.863	0.000	1.493	0.000
13 Production and specialised services managers	2.98	0.0358	2.149	1.696	1.785	1.491	1.985	1.360	1.760
14 Hospitality, retail and other services managers	2.05	0.071	1.910	1.711	1.576	0.656	1.940	1.432	1.529
21 Science and engineering professionals	3.58	0.0043	1.456	1.149	1.851	1.898	0.000	0.000	1.643
22 Health professionals	3.56	-0.276	1.941	0.766	0.926	1.423	0.000	1.313	0.000
23 Teaching professionals	6.63	-0.162	0.809	0.638	0.771	0.791	1.447	1.095	1.141
24 Business and administration professionals	3.76	-0.064	1.819	1.595	1.736	1.779	1.809	0.000	1.882
25 Information and communications technology professionals	2.12	-0.242	1.941	0.000	1.620	2.135	0.000	1.478	1.848
26 Legal, social and cultural professionals	3.22	-0.240	1.348	1.064	1.286	1.318	1.930	1.277	1.825
31 Science and engineering associate professionals	3.44	-0.140	0.871	1.522	1.306	1.703	1.781	1.473	1.632
32 Health associate professionals	2.59	-0.123	0.849	1.053	1.157	1.067	1.303	1.478	1.027
33 Business and administration associate professionals	6.34	-0.038	1.875	1.740	1.683	1.474	2.007	1.368	1.836
34 Legal, social, cultural and related associate professionals	2.59	-0.117	1.356	0.901	1.021	0.767	1.341	1.207	1.148
35 Information and communications technicians	0.80	-0.196	1.617	1.595	1.543	1.581	0.000	1.095	0.000
41 General and keyboard clerks	2.54	-0.079	1.248	1.367	0.727	0.746	2.109	1.173	1.819
42 Customer services clerks	2.86	-0.046	1.266	1.373	1.207	0.825	1.935	1.392	1.607
43 Numerical and material recording clerks	3.63	0.003	1.115	1.320	1.250	0.791	1.397	1.170	1.275
44 Other clerical support workers	2.59	-0.108	1.115	1.552	1.188	0.962	1.819	1.376	1.665
51 Personal service workers	4.56	0.045	1.213	0.947	0.649	0.290	0.875	0.896	0.660
52 Sales workers	7.03	0.086	1.574	1.344	0.954	0.542	1.249	1.146	0.813
53 Personal care workers	7.05	-0.185	0.416	0.580	0.410	0.474	1.303	1.051	0.986
54 Protective services workers	1.65	-0.340	0.527	0.624	0.252	0.980	1.510	1.463	1.384
61 Market-oriented skilled agricultural workers	1.50	-0.008	1.431	1.031	0.860	0.669	1.169	1.074	1.027
71 Building and related trades workers, excluding electricians	3.88	0.047	1.028	1.062	0.990	1.202	0.863	1.104	0.610
72 Metal, machinery and related trades workers	2.71	0.021	0.767	1.194	0.910	1.440	0.891	1.221	0.702
73 Handicraft and printing workers	0.41	-0.045	0.539	1.276	0.900	0.791	0.724	1.186	0.570
74 Electrical and electronic trades workers	1.56	-0.112	0.866	1.367	1.075	1.949	1.473	1.525	1.027
75 Food processing, wood working, garment and other craft	1.22	0.0368	0.749	0.788	0.545	0.314	0.798	0.869	0.544
81 Stationary plant and machine operators	1.80	-0.061	0.299	0.922	0.657	0.820	0.831	1.074	0.659
82 Assemblers	0.52	0.008	0.105	0.916	0.704	1.135	0.661	0.999	0.536
83 Drivers and mobile plant operators	3.01	-0.039	0.644	0.847	0.591	1.198	1.063	1.266	0.674
91 Cleaners and helpers	2.67	-0.065	0.223	0.147	0.083	0.194	0.609	0.670	0.377
92 Agricultural, forestry and fishery labourers	0.59	0.004	0.418	0.297	0.279	0.164	0.037	0.368	0.071
93 Labourers in mining, construction, manufacturing and transpo	2.31	-0.046	0.501	0.740	0.478	0.554	0.753	0.974	0.507
94 Food preparation assistants	0.67	-0.037	0.871	0.442	0.356	0.182	0.779	0.884	0.737
95 Street and related sales and service workers	0.05	0.348	0.000	0.957	1.157	0.000	0.000	0.000	0.000
96 Refuse workers and other elementary workers	0.93	-0.074	0.428	0.450	0.499	0.837	0.979	1.062	0.604
Mean			1	1	1	1	1	1	1
Minimum			0	0	0	0	0	0	0
Maximum			2.291	1.740	2.104	2.135	2.109	1.551	1.940

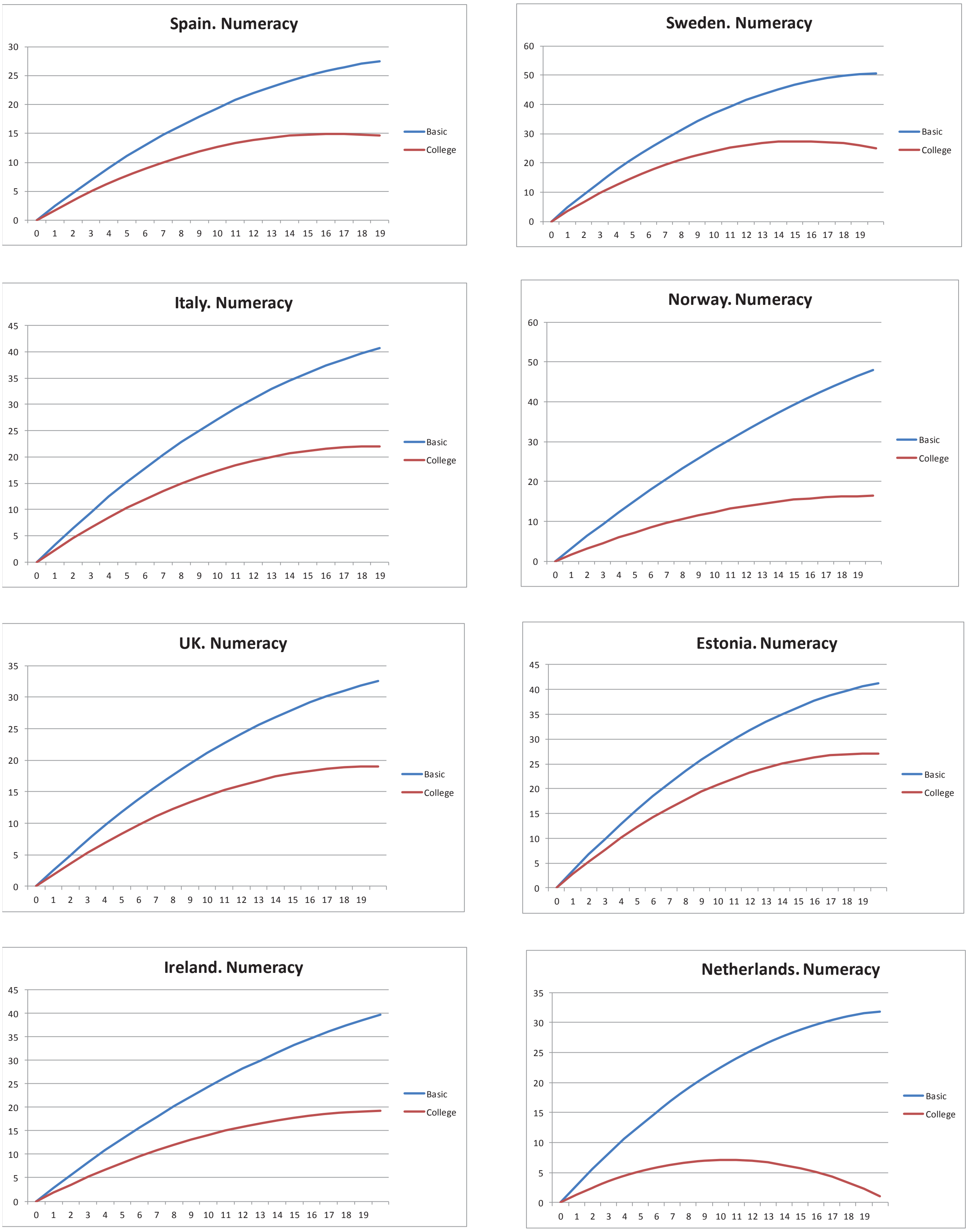
Source: PIAAC

Footnotes:

a. Sample of respondents with basic schooling 16 to 45 years old that report their current or last occupation.

b. Tasks has been summarized using Principal Component Analysis. Main numeracy tasks (weights) 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).

Figure 1: The impact of working experience on numeracy scores, by country



Source: PIAAC, selected countries

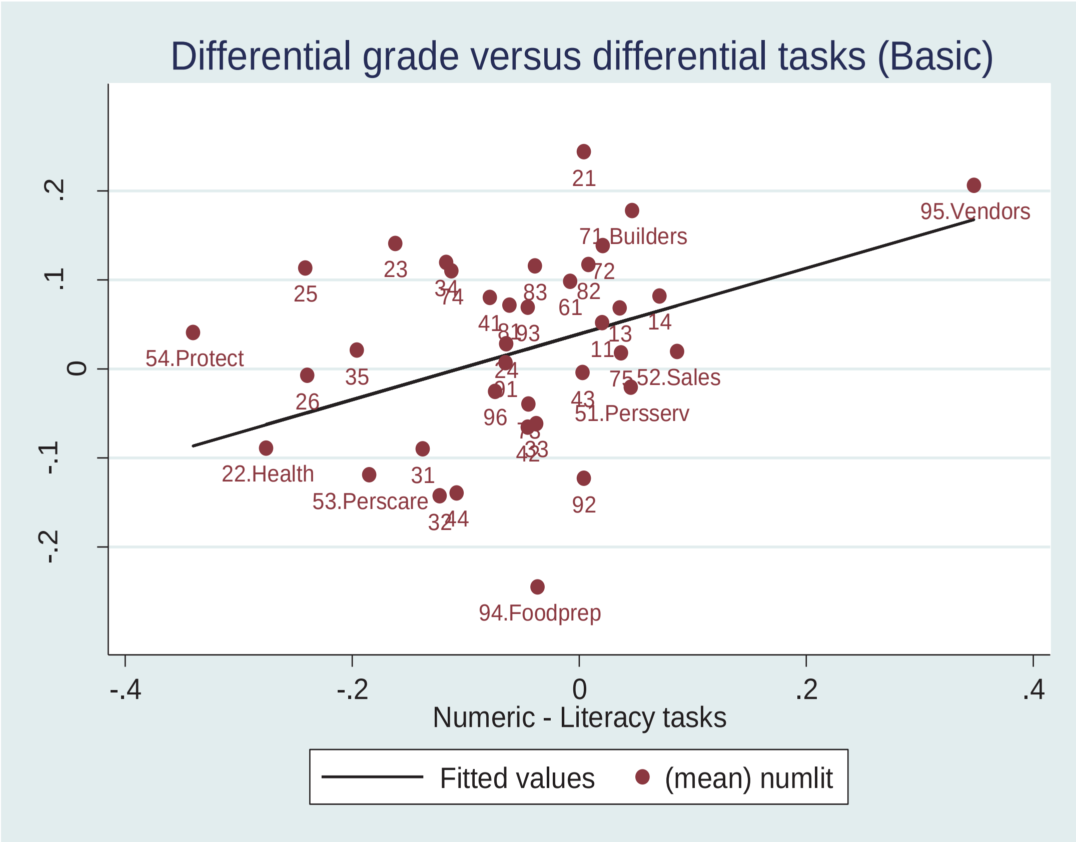
Footnotes:

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.

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 2: Differential numeracy-literacy score versus differential tasks by occupation (Basic schooling)



Source: PIAAC

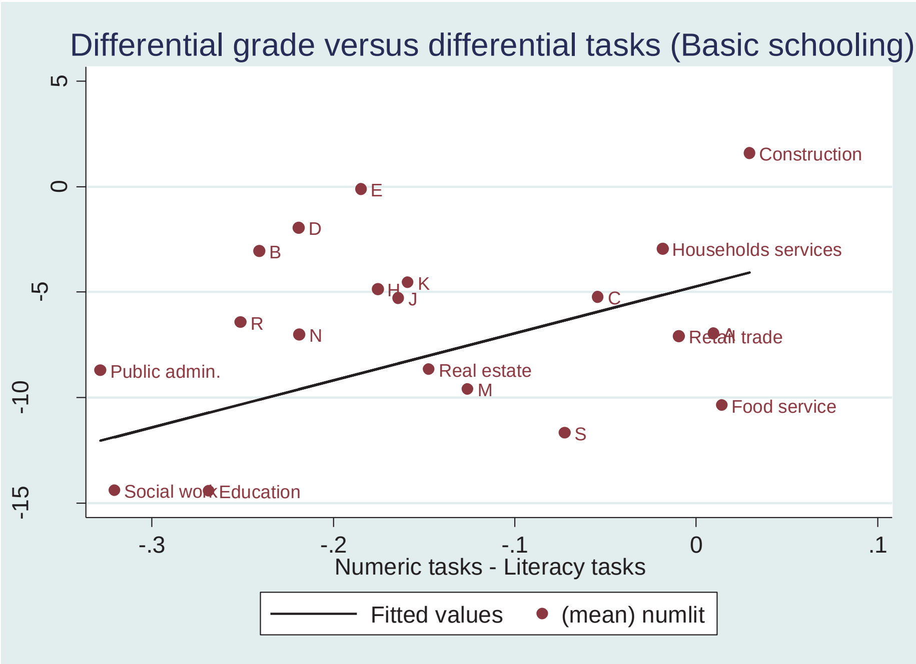
Footnotes:

a. Sample includes respondents of 16 to 45 years old with basic schooling.

b. Observations from Spain, Italy, Ireland, UK, Sweden, Norway, Estonia and Netherlands, countries with large enough samples of individuals with basic schooling.

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 3: Differential numeracy-literacy score versus differential tasks by industry



Source: PIAAC

Footnotes:

a. Sample includes respondents 16 to 45 years of age who have just completed compulsory schooling.

b. The differential score 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 performed at least once during the last month relative to the proportion of reading tasks

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