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ABSTRACT

Task Specialization and Cognitive Skills: Evidence from PIAAC and IALS*

We study how the tasks conducted on the job relate to measures of cognitive skills using data from 18 countries participating in the Programme for the International Assessment of Adult Competences (PIAAC) and from 13 countries that also participate in the International Adult Literacy Study (IALS). We document two main findings. Firstly, individual- fixed effect models suggest that low-educated workers in jobs involving a particular set of basic tasks -say, in numeric rather than reading or ICT tasks- obtain 10% of one standard deviation higher scores in the domain of the PIAAC assessment most related to those tasks than in the rest -say, numeracy relative to literacy or problem-solving scores. The estimates are weaker for workers with a high school or college degree, those with more than 10 years of experience or who are males. Secondly, a synthetic cohort analysis using repeated literacy assessments in IALS and PIAAC indicates that, among the low-educated, long-run increases in the reading task component of jobs correlate positively with increases in cohort-level literacy scores. An interpretation of our findings is that tasks conducted on the job help in building human capital. Under that interpretation, our back-of-the envelope estimates suggest that the contribution of one year of on-the-job learning to skill formation is between a half and a fourth of an extra year of compulsory schooling.

JEL Classification: J24, J31, I20

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

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1 Introduction

Workers obtain skills both in the formal education system and by learning on-the-job.[1] While there is a substantial literature on how schooling raises cognitive skills and, in turn, wages, much less is known about how skills are formed by learning on the job.[2] For example, it is well known that wages increase with labor market experience, that the monetary return to experience is typically higher for workers with college and it is lower in low-income countries than in high income countries (see Lagakos et al, 2018). In addition, the monetary return to experience is lower the larger the size of a cohort -see Jeong et al (2018). As those studies point out, heterogeneity in experience profiles could be due to search frictions, to increased competition for jobs or, alternatively, to differences in human capital accumulation -related, for example, to the task content of jobs.

Our study uses data on actual tasks conducted on the job and different measures of cognitive skills to study the link between tasks and cognitive skills. We rely on measures of cognitive ability of representative samples of the population of eighteen countries participating in PIAAC, an OECD-coordinated effort to measure the skills of the population between 16 and 65 years of age. We measure human capital through three cognitive measures in standardized tests: numeracy skills, literacy skills and problem-solving skills in technology-rich environments. The availability of three different measures is important, as it allows us to relate specific tasks to skills while holding constant an individual-fixed effect.

We think that measures of cognitive skills are an important source of information because of two reasons. The first is that measures of cognitive abilities are available for representative samples of the population that include the long-term unemployed.[3] Conceptually this is important, as the accumulation of human capital by low-skilled is an important policy parameter that may be difficult to measure using wages -as that group is more likely to be affected by non-employment -see Charles et al. (2016). In addition, by proxying human capital with measures of cognitive skills, we avoid econometric problems related to modeling labor market participation. Still, the literature has documented that the skill measures we use are indeed related to wages. For example, Leuven et al. (2004) document that cross-country variation in the net supply of skills -as measured by the International Adult Literacy Survey- correlates negatively with wages, a relationship that is especially strong among low-skilled workers.

[1] See Mincer (1974), Rosen (1972), Becker (1964) and Ben Porath (1967).

[2] See Card (1999), Angrist and Krueger (1991), Carneiro et al. (2011), Murnane et al. (1995)

[3] 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). Also it may depend on the age of the worker when facing the unemployment spell. See Arellano-Bover (2020). As PIAAC collects information about the task content of the last job of unemployed respondents, we are able to include those workers in the analysis.

An interpretation of the finding is that cognitive skills are indeed priced by the labor market. In addition, Hanushek et al. (2015) also document that numeracy skills are positively associated to wages in the twenty-three countries participating in PIAAC.

Our empirical strategy draws from the literature that estimates education production functions by using multiple measures of skills. In particular, we estimate the contribution of on-the-job learning on human capital by exploiting the availability of multiple measures of cognitive skills for the same individual and the fact that jobs vary in their task content.[4] For example, we estimate the effect of the relative intensity of numeric (relative to reading) tasks on the job on the relative score in numeracy (versus literacy) tests, using a specification that absorbs any individual-level characteristic that is constant across human capital measures.[5] We do similar exercises to test if workers in ICT intensive jobs perform better in the problem solving part of the test than on the literacy part.

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 or problem-solving skills that lead workers to select into jobs with a higher numeracy content[6]. To get a sense of the magnitude of that selection bias, we use various methods. The first method assumes 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 -we provide some evidence on this regard. As a result, any differential performance in numeracy tests relative to literacy or problem-solving tests associated to specialization in basic numeric tasks among college or high-school workers may reflect sorting across jobs, allowing us to assess to what extent our estimates reflect biases due to selection. A second method combines information from the literacy assessments in the 1994 International Adult Literacy Survey (IALS) and in PIAAC as well as information about the reading and numeric component on jobs to construct synthetic life-cycle profiles of reading tasks and literacy scores -see Barrett and Riddell (2016). We then regress cohort-level changes in literacy scores on the cohort-level changes in the reading content of jobs. That specification holds constant the unobserved initial stock of literacy at the cohort level, and identifies the impact of job content on literacy skills us-

[4]We do not model the role of non-cognitive skills - Cunha and Heckman (2007). However, we control in the analysis below for related variables, like the respondent's assessment about his or her own interest in learning about new things.

[5]In a different, but related setting Silva et al. (2012), Bietenbeck (2014) or Metzler and Woessman (2012) exploit the availability of multiple measures of cognitive skills and differential exposure across subjects to estimate the impact of peers or teacher characteristics on on test scores.

[6]See Lise and Postel-Vinay (2020), who estimate a model on longitudinal data where workers are endowed with bundles of skills that have different returns depending on job requirements. Sorting across jobs plays an important role in accounting for lifetime output of a worker.

ing an alternative set of assumptions from those in the worker fixed-effect model.

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 or problem solving tests (and viceversa). Namely, respondents with basic schooling who fully specialize in basic numerical tasks on their jobs obtain between 7% and 10.8% of one standard deviation higher scores in the numeracy test than in the literacy test. On the other hand, in our preferred sample of individuals with less than 10 years of experience, 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. The relationship is also stronger among females.We interpret from the methods outlined above that around a third of the estimated impact is due to sorting biases.[7]

An interpretation of our findings is that on-the-job learning by conducting basic numerical, reading or ICT tasks is a substitute for formal education for workers with compulsory schooling. We draw on evidence in previous studies to obtain a tentative estimate of the degree of substitution between of one year of formal education and between two and four years of skill acquisition on the job. The rest of the paper is organized as follows. Section 2 describes the test. Section 3 describes the datasets. Section 4 discusses the link between between tasks on-the-job and numeracy and literacy scores. Section 5 splits tasks into basic and advanced ones. Section 6 discusses how we deal with biases due to sorting. Section 7 presents the main conclusions.

2 Empirical methods

We assume that human capital C_i is acquired by an individual i through the formal education system (that we denote as S_i) and by the task-content of his or her job, denoted by J_i. Individuals may also vary in their initial endowment of human capital, $C_{0,i}$, a measure that summarizes factors related to the innate ability of a worker.

$$C_i = \alpha_0 + \alpha_1 S_i + \alpha_2 J_i + \alpha_3 J_i * S_i + C_{0,i} + \epsilon_i$$

As in Mincer (1974), the tasks performed on-the-job and formal schooling S_i may affect the stock of acquired skills C_i in a non-linear fashion. On one hand, the tasks learnt on-the-job could complement formal education if it is mainly highly skilled individuals who enhance their skills from performing sophisticated

[7] One important caveat about our estimations is that 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.

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, alternatively, through practice on-the-job. We use three different proxies of human capital, C_i, measured through numeracy, literacy and problem-solving scores in standardized tests ($C_{n,i}$, $C_{l,i}$ and $C_{p,i}$ respectively). That means that we observe

$$C_{m,i} = \alpha_{0,m} + \alpha_{1,m} S_i + \alpha_{2,m} J_i + \alpha_{3,m} J_i * S_i + C_{0,i} + \epsilon_{mi}, \quad m = n, l, p \quad (1)$$

We focus on three different measures of tasks performed on each respondent's current or last job: ICT-related ($J_i = p_i$) reading-related ($J_i = l_i$), numeracy-related ($J_i = n_i$). $C_{0,i}$ captures a set of initial skills that affect equally all sorts of cognitive skills (problem-solving, reading or numeracy-related). ϵ_{mi} is a mean-zero unobserved factor reflecting the initial endowment of domain-specific human capital, uncorrelated with the initial amount of general human capital $C_{0,i}$.[8]

We gauge the skill gain of workers with basic schooling by examining how the task content of their job (either p, 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 jobs -i.e., for the whole history of numeracy or literacy tasks performed in different jobs. However, we deal with at most repeated cross sections 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 potential working experience.

The parameter of interest. We focus on $\alpha_{2,m}$, the impact of domain-specific tasks done on the job (reading, numeric and ICT) on domain-specific cognitive skills $C_{m,i}$. Several reasons lead us to expect that $\alpha_{2,m}$ varies across individuals. We already mentioned that $\alpha_{2,m}$ 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.

2.1 Controlling for unobserved heterogeneity

A problem when estimating model (1) is that the failure to hold pre-labour market ability $C_{0,i}$ constant is likely to result in an upward bias of OLS estimates

[8]Model (1) deals with numeracy, literacy and problem solving 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, as discussed below, one key assumption is that the impact of literacy tasks on literacy scores is similar to the impact of numeric (ICT) tasks on numeracy (problem solving) scores. That assumption is hard to implement in non-linear settings

of $\alpha_{2,m}$ in Model (1).[9] We exploit multiple measures of human capital for the same individual to control for $C_{0,i}$. Under Assumption 1, $\alpha_{2,m}$ can be estimated by analyzing if workers in jobs with a relatively higher numeracy content -relative to its reading or ICT one- end up with a relatively higher numeracy score -relative to their scores in the literacy or problem-solving assessments.

Assumption 1: The impact of conducting reading (ICT) tasks on literacy (problem-solving) scores equals the impact of mathematical tasks on numeracy scores

In other words, assumption 1 states that $\alpha_{2,n} = \alpha_{2,l} = \alpha_{2,p}$ and that $\alpha_{3,n} = \alpha_{3,l} = \alpha_{3,p}$ Then, one can take the difference between any pair of skills (say, numeracy vs literacy):

$$C_n - C_l = [\alpha_{0,n} - \alpha_{0,l}] + [\alpha_{1,n} - \alpha_{1,l}]S + \alpha_2[n - l] + \alpha_3[n - l] * S + \epsilon_n - \epsilon_l \quad (2)$$

Model (2) identifies the impact of tasks performed on-the-job on particular forms of human capital (numeracy vs literacy) by comparing individuals who have different degrees of *specialization* in the tasks they perform in their jobs (in the example, numeric vs reading tasks, or $n - l$, but we can also estimate $n - p$ and $l - p$). We discuss below how plausible Assumption 1 is.[10] .

A second consideration in Model (1) is that workers sort in the labour market according to their initial endowment of domain-specific human capital. In other words, workers with an initial ability for numeracy-related jobs may sort into numeracy-intensive jobs. A higher value of $\epsilon_n - \epsilon_l$ -i.e., workers who have a higher comparative advantage in numeracy tasks- are likely to sort into a relatively math-intensive work environment -i.e., with a higher level of [n-l]. Sorting would generate a positive correlation between the numeracy content of a job and initial endowment of numerical human capital. We discuss alternative ways to assess the magnitude of such selection bias.

2.1.1 Method 1: Comparing groups with different ability to select across jobs

Experience in the labor market indicates the ability to sort across jobs. Hence, all our specifications present results for two samples: individuals with less than 10 years of potential working experience and with more than ten years. Respondents who have completed compulsory schooling at most and are in their first 10 years of potential working experience have had less time to sort across jobs

[9] A possible reason is sorting on general ability if firms retain better workers. Arellano-Bover (2020) documents lower cognitive scores among workers who started their careers at times of higher levels of unemployment, possibly due to starting matches with smaller, worse firms. That could be a reason for an upward bias in the estimation of $\alpha_{2,m}$ in models without individual fixed effects.

[10] In particular, an individual fixed-effect model absorbs cohort-level changes in the general ability of workers. See Green and Riddell (2013) for a discussion in the context of parsing out life-cycle and cohort effects in skill accumulation.

than the rest of workers, but still have accumulated experience so that their skills have been affected by exposure to math- or reading- intensive environments.[11]

The second way to assess the role of selection bias using a model along the lines of Roy (1951). 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 reading- related tasks)[12]. Workers care about the monetary return of a job and about a non-monetary component n that captures the types of tasks on the job. The utility from that non-monetary aspect is $v[n]$, so $u(w_n, n) = w_n + v[n]$

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, a personal care worker). Under those assumptions, conditional on choosing a numeric job, the gap in cognitive skills in math and, say, numeracy can be written as:

$$E(C_n - C_l|n = 1) = \alpha_2 n + E\{\epsilon_n - \epsilon_l|\epsilon_n - \epsilon_l > \frac{v[n] - v[0]}{w}\} \qquad (3)$$

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 (α_2 under Assumption 1) or because of a sorting process 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.[13] [14]

A possible strategy to identify α_2 is to identify a group of the population for which the difference between measured numeracy and literacy (ICT) skills could be attributed to selection. Consider the case of workers with a college degree. Those workers may end up with higher numeracy skill levels -relative to literacy or problem-solving ones- due to their initial endowment of numeracy

[11] An alternative cut-off of the sample is age. The advantage of using potential experience is that human capital models predict accumulation in the first years in the labor market (which may happen at different ages, depending on the level of schooling).

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

[13] See Lise and Postel-Vinay (2020) on the wage dynamics implied by the match between skills of a worker and job requirements.

[14] The expression (3) can be obtained assuming that there is a market return to ability, above and beyond schooling or other covariates $w_n = wC_n$ 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

$$C_n - C_l > \frac{v[0] - v[n]}{w}$$

In other words, a worker will choose a numeracy job when the wage return to her numerical ability -relative to the literacy one- exceeds any possible utility loss from conducting numeric, rather than literacy tasks. Further using Model (1), together with $C_n = \alpha_2 n + \epsilon_n$ and $C_l = \epsilon_l$ one can obtain expression (3) in the text.

or because their choice of electives but not, we assume, because their jobs have involved 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 score, 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 (or problem-solving) 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 or problem-solving 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 or problem solving 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

$$\begin{aligned} E(C_n - C_l | n_s &= 1, S = high\_school, tertiary) \\ &= E(\epsilon_n - \epsilon_l | \epsilon_n - \epsilon_l > \frac{v[n] - v[0]}{w}, high\_school, tertiary) \end{aligned}$$

where $n_s = 1$ indicates that the job involves conducting a simple numeracy task. So 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 or ICT 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 the assumption 2, the coefficient of simple tasks in that sample reflects sorting. We repeat those exercises for numeracy vs problem solving skills (by comparing scores in numeric jobs vs ICT intensive ones) and literacy vs ICT.

Assumption 3: The degree of selection across jobs among high school or college workers is similar to that of primary school workers

More exactly, what we need is that selection across jobs is not stronger among workers with primary schooling than among workers with high school or a college degree. Using that assumption, we can subtract the sorting component from the estimates in the first step to get an estimate of the impact of doing tasks on the job on cognitive skills.[15] 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:

$$\hat{\alpha}_{2,basic} = \alpha_2 + \frac{E[(n-l)(\epsilon_n - \epsilon_l)]}{Var(n-l)}$$

On the contrary, for workers with high school or college, $\alpha_2 = 0$, so an OLS regression of $C_n - C_l$ on $(J_n - J_l)$ yields $\hat{\alpha}_{2,highschool} = \frac{E[(n-l)(\epsilon_n-\epsilon_l)]}{Var(n-l)}$ Hence, a comparison between $\hat{\alpha}_{2,basic}$ and $\hat{\alpha}_{2,highschool}$ can be interpreted as a quantification of the degree of sorting of individuals across jobs. 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 discuss below how realistic assumptions 2 and 3 are.

When taking fixed-effects models to the data, we make several notes. The worker fixed-effects model assumes that worker-specific covariates -age, gender- have similar impacts on cognitive skills in the numeracy and literacy domains. To account for the possibility that these covariates affect numeracy, literacy and problem solving skills differently we including controls such as age, potential work experience and some measures of non-cognitive abilities. 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 (2) we control for the presence of *advanced* tasks on-the-job.[16]

2.1.2 Method 2: Using synthetic cohorts to control for the initial endowment of human capital

An alternative method to control for initial human capital endowments is to use repeated measures of cognitive abilities over time. For example, using several realizations for the same individual, we could control for $C_{0,i} + \epsilon_l$ by taking differences over time. Unfortunately, repeated observations on cognitive skills are not available at the individual-level. Nevertheless, the repeated country-specific assessments in IALS (1994) and PIAAC (2012) make it possible to track cohort-level changes in the evolution of literacy skills and the task content of jobs over the life-cycle in thirteen countries. In particular, taking cohort-specific averages

[15] Obviously, under the assumption that $\alpha_2 = 0$ for individuals with high school or college. Model (2) cannot establish whether simple tasks increase human capital differentially for individuals with high school or college

[16] 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.

in Model (1)

$$\overline{C}_{l,c,t} = \alpha_{0,l,t} + \alpha_l \overline{J}_{l,c,t} + \overline{C}_{0,c} + \overline{\epsilon}_{l,c} \tag{4}$$

A hat over a variable denotes its cohort-specific mean (i.e., $\overline{C}_{l,c,t} = \sum_i \frac{C_{l,i,t}}{N_c}$ is the cohort-specific average of the literacy score and $\overline{J}_{l,c,t} = \sum_i \frac{J_{l,i,t}}{N_c}$ the cohort-level mean of tasks). We define cohorts as groups of respondents sharing (10-year) date-of birth, country, education level and gender. Drawing on multiple observations for the same cohort over time, one can take within-group differences and estimate $\alpha_{(2,l)}$ as follows.

$$\overline{C}_{l,c,2012} - \overline{C}_{l,c,1994} = \Delta\alpha_0 + \alpha_l[\overline{J}_{l,c,2012} - \overline{J}_{l,c,1994}] + \overline{\epsilon}_{l,c,2012} - \overline{\epsilon}_{l,c,1994} \tag{5}$$

The term $\Delta\alpha_0 = \alpha_{0,l,2012} - \alpha_{0,l,1994}$ captures any cohort-level deterioration of literacy skills over the life-cycle (see Green and Riddell, 2013), while $\overline{J}_{l,c,2012} - \overline{J}_{l,c,1994}$.reflects changes in the reading requirements of jobs over time. Unlike Model 1, changes in $\overline{J}_{l,c,2012} - \overline{J}_{l,c,1994}$are unlikely to reflect sorting of individuals across jobs, as it is hard to think that members of a cohort systematically look for the same type of jobs. Nevertheless, to test for the presence of biases due to correlation between $\overline{\epsilon}_{l,c,2012} - \overline{\epsilon}_{l,c,1994}$ and $\overline{J}_{l,c,2012} - \overline{J}_{l,c,1994}$ we control for changes in numeracy requirements of tasks on the job measured both in IALS (1994) and in PIAAC (2012). Under the assumption that α_l mainly picks up the reading content of jobs, it should not be affected by whether or not we introduce other indicators of the task contents of jobs, such as the numeracy. Thus we run an alternative model and test if the numeracy content of jobs explains the increase in literacy.

2.2 Discussion of the assumptions

Assumption 1: The impact of conducting reading(ICT) tasks on literacy(Problem-solving) scores equals the impact of math tasks on numeracy scores

There are several reasons why this assumption may fail. Firstly, one may imagine that some of the tasks are easier to measure than others. Whereas using a calculator is straightforward to remember and report, some respondents may have different interpretations of whether or not they "read a diagram" or how often they do that tasks. If reading tasks were poorly measured but numeric tasks were not, the fixed-effect interpretation would not really measure the impact of specialization on differential performance in the test. However, the availability of various measures of tasks and skills allows us to test Assumption 1 fails. We can estimate for each schooling group

$$C_m - C_q = [\alpha_{0,m} - \alpha_{0,q}] + \alpha_2[m-q] + \epsilon_m - \epsilon_q \qquad for \qquad m \neq q, m = n, l, p \tag{6}$$

That is, comparing the impact of specialization in numeric vs reading tasks on numeracy vs literacy scores to the estimate of specialization in reading (vs

ICT) tasks on literacy (vs problem solving) scores If Assumption 1 holds α_2 should be very similar across all models. In addition, we estimate Model (1) separately for numeracy, literacy and problem solving scores. Those regressions provide (possibly biased) estimates of the impact of a math-intensive environment on numeracy scores and, separately, of a reading-intensive environment on literacy scores. Both specifications (pairwise differences in scores vs tasks and specification in levels) serve as a test of whether the task-coefficients in all models are of broadly similar magnitude.

Assumptions 2 and 3: Performing simple numeric tasks at the job does not have a causal effect on the difference between numeracy and literacy (or problem-solving) skills for workers with a college or high school degree

Those assumptions are key in obtaining the result that differences in the presence of simple tasks across jobs reflects sorting, not differences in productivity. The idea that workers sort into jobs that match their skills is supported by German panel survey data. For example, few German workers move voluntarily to jobs requiring skills different from those they have and those who do require sizable wage increases -see Villanueva (2007). However, one could challenge the notion that performing simple tasks on the job does not affect the productivity of respondents with either high-school or college. A positive impact of performing simple task on human capital implies that the correlation between both variables among high school respondents would pick up not only sorting components, but also productivity. In such case, we would be *overcorrecting* for sorting and our procedure would provide a lower-bound of the true impact of working in jobs that are pervasive at math (reading) tasks on the accumulation of numeracy (literacy) skills. A more serious problem would arise if differences in the presence of simple tasks across jobs reflected misallocation of workers to jobs, or overeducation (in which case α_2 would be even negative for high-school or college workers). The existing literature we are aware of is not conclusive about the extent and consequences of overeducation -see Mahuteau et al (2013) or Leuven and Osterbeek (2011).

Finally, one can raise the objection that workers with a college or high school degree have different ability to sort across jobs than workers with basic schooling. 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.

Assumptions implicit in synthetic cohort models

An alternative to Assumptions 2 and 3 is to use synthetic cohorts to control for the initial endowment of human capital. Any analysis based on the evolution of synthetic cohorts requires that respondents in different assessments represent the same underlying population. We take several measures to guarantee that this is indeed the case. Firstly, to guarantee that literacy skills are comparable to each other we use the re-scaled version of IALS, explicitly designed for the purpose -see OECD (2013) and the application in Barrett and Riddell (2016). Secondly, we define groups whose schooling is not likely to have varied much over time. Hence, we use individuals who are 25-34 years of age in IALS (cohorts born between 1960 and 1969) and 35-44 years (cohorts born between 1950 and 1959). By age 25, the schooling composition of a cohort is basically constant over time, as most individuals have finished their studies. Those cohorts are observed 18 years later in PIAAC (i.e., when the 1960-1969 cohort is 43-52 years of age and the 1950-1959 cohort is 53-62 years of age). A final concern is that the probability of individuals dropping from the labor force, so tasks measured at each point in time belong to a different working population. To that end, as in the rest of the paper, all PIAAC samples include individuals who are either currently working or who have stopped working in the last year.

3 Database

The main 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 use 18 countries: Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Korea, Netherlands, Norway, Slovak Republic, Spain, Sweden, USA and the United Kingdom (namely, England and Northern Ireland).[17]

In each country a representative sample of adults between 16 and 65 years took a direct assessment of their proficiency in literacy and numeracy. The "literacy" assessment excludes the ability to write, but goes beyond reading ability by measuring "the range of cognitive strategies (...) that adults must bring into play to respond appropriately to a variety of texts of different formats". Numeracy measures the ability of "managing a situation or solving a problem in a real context by responding to mathematical information and content represented in multiple ways".[18] The "problem solving" assessment measures the ability of individuals to solve problems that arise using ICTs (...), where prob-

[17]We do not use data on Russia as the data is not really comparable to the rest (see OECD, 2013). The questionnaires in Japan and Poland did not ask about the tasks workers do at their job, so they lack essential data for the analysis.

[18]All excerpts from OECD (2013). The exact definition of literacy is "understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential". Numeracy is defined as "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life".

lems are a consequence of the availability of new technologies (...) and require the use of computer-based artifacts (...)". Of the countries surveyed, France, Italy and Spain did not include that assessment, so we omit those countries in any model including problem-solving scores (but not in the rest). The survey was implemented either by computer or on paper and pencil.[19]

In addition, PIAAC contains internationally comparable information about the educational attainment of individuals as well as about the tasks performed in the current or last job. We use questions about tasks on the job to construct measures of the numeracy, reading and ICT task content of jobs.

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, reading or ICT related. Numeracy-related tasks include elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams, elaborating graphs or using algebra. We classify as literacy-related tasks reading email, reading guides, reading manuals, writing emails, writing reports, reading articles, reading academic journals, reading books and writing articles. Finally, ICT tasks involve using email, using internet, processing texts, conducting transactions over internet, programming and using spreadsheets.

We also distinguish between basic and advanced tasks using principal component analysis, as their impact on human capital accumulation is likely to vary across educational groups. Regarding numerical tasks, we classify tasks into advanced and basic, and identified elaborating a budget, using a calculator, reading bills, using fractions or percentages and reading diagrams as basic tasks. Conversely, we classify elaborating graphs or using algebra as advanced tasks.[20] 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. Regarding ICT tasks, we classify using email, using internet and conducting transactions over internet as basic, and programming, processing texts and using spreadsheets as advanced tasks.[21]

[19]We control for a dummy that indicates whether the individuals conducted the exam on paper.

[20]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.

[21]Following the same strategy as with numeracy, the first factor put equal weights on all tasks while the second factor weighted only the advanced mentioned, letting us classify them into advanced literacy or ICT tasks. These two factors explain around a 60% (in the case of literacy) and 70% (in the case of ICT) of total variance.

We construct two different measures of task intensity on the job. The first simply computes 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 bills, reads a diagram, uses a calculator, and computes a fraction or percentage in her current or last job) we grant her 1(=5/5) in "Basic math tasks". If she conducts only one of the five tasks, we grant her 0.20=(1/5). For example, around 15% of low educated workers in the overall sample are granted one. We define "Basic literacy tasks" and "Basic ICT tasks" in a similar fashion. The degree of specialization is defined as the difference between "Basic math tasks", "Basic literacy tasks" or "Basic ICT tasks".[22]

Formal education. We group individuals in three schooling levels, following a classification elaborated by the OECD. 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 Training 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. Finally, we exclude from the sample respondents without labour market experience. The resulting sample contains 83,811 individuals in those 18 countries. Sample sizes per country vary between 19,566 in Canada and 2,737 in Sweden.

3.1 Summary statistics in PIAAC

Table 1 shows summary statistics for the 18 countries that conducted the numeric and literacy scores. The fraction of prime workers with basic schooling is 19% in the full sample, being highest in Spain (43%) and lowest in the Czech Republic (6%). The average number of years worked does not change much

[22]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. We construct 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.

across countries, in contrast.

Figure 1 shows the fraction of individuals who report having performed in their current or last job one of the basic tasks, by schooling group. As expected, the fraction of individuals who report having performed a basic task is larger among those with basic schooling than among those with college. Excluding Finland, Czech and Slovak Republic, between one quarter and one third of individuals with basic schooling perform at least one of the simplest numeric (reading) 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.[23] The most common basic tasks are using fractions, a calculator, and elaborating budgets (not shown). Conversely, among individuals with high educational levels, the most common advanced numeric task is preparing graphs, while reading books or academic journals is the most prevalent advanced literacy-related task.

Thus, the statistics in Figure 1 suggest that, in most of the countries we consider, a nontrivial share of individuals with basic schooling perform simple tasks at their jobs, thus having at least the possibility of using and acquiring some skills.

3.2 Evidence from the International Adult Literacy Survey (IALS)

To implement the synthetic cohort analysis, we combine information from two assessments on Literacy: the 1994 International Adult Literacy Survey (IALS) and the already mentioned PIAAC. We use thirteen countries that are present both in IALS and PIAAC: Belgium, Canada, Czech Republic, Denmark, Finland, Germany, Ireland, Italy, Netherlands, Norway, Sweden, United Kingdom and the United States. The rescaled version of IALS has been designed so that measures of literacy cognitive skills (the only ones available in IALS) are comparable to those in subsequent assessments (in particular, ALL and PIAAC). All measures are in a 0-500 scale.

IALS also asks to respondents who have been employed for the last twelve months about how frequently they perform certain tasks in their jobs in a manner that is comparable to the questions posed in PIAAC. In particular, we use the following reading or writing-related tasks: reading letters or memos, reading reports, articles or manuals, writing letters and writing reports or articles. IALS also includes tasks that we classify as numerical, such as reading bills, reading diagrams or using math to compute costs or budgets. Finally, the OECD has

[23]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 (not shown)

elaborated a classification of schooling levels that is comparable across assessments, which is the one we use for this part of the analysis.

We use individuals born between 1950 and 1969, as they would still be below 65 years of age eighteen years after the IALS assessment, once PIAAC is conducted. We aggregate observations in cells defined by 10-year birth cohorts, schooling level, gender and country. For shorthand, we assign the IALS and PIAAC measurements of the 1950-1959 cohort to 40 and 55, respectively. Abusing notation, we assign the ages to the 1960-1969 cohort to 25 years in PIAAC (the average would be 30) and 55 in IALS (the average age would be 47).

Figure 2 presents cohort-level measures of the use of reading- and writing-literacy skills on the job in both assessments. This is shown for non-college workers in selected countries in the sample.[24] The (frequency-adjusted) use of reading skills either increases to or stays constant around 40% between ages 25 and 40 (there are mild decreases in Canada and Finland). Between the ages 40 and 55, there is a great deal of heterogeneity, but typically the increase in the use of reading skills was milder between those ages than between 25 and 40 (see for example, Canada, Denmark, Sweden or Norway).[25] We use that heterogeneity in life-cycle profiles across cohorts to identify the response of literacy scores to the use of reading skills.

4 Job tasks and cognitive skills

This section investigates the impact on relative performance in numeracy vs literacy tests of the relative specialization in numeracy tasks on the job. We start by comparing the measures of tasks across occupations and investigate their correlation with the test scores. To implement Model (2) we need that the numeracy, literacy and problem-solving 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. We provide now evidence that supports the notion that different jobs involve different bundles of numeracy, reading and ICT tasks, paying special attention to those available for the least skilled.

[24] Sample sizes are smaller when we consider workers with primary schooling only, so we illustrate the main patterns pooling primary and secondary schooling. In the empirical analysis, we regress education-specific changes in literacy scores on education-specific changes in the use of reading tasks.

[25] Note that younger cohorts use substantially more reading skills at their jobs than older ones in particular countries. In particular, cohort effects are noticeable in Nordic countries but Finland and the United States or Italy.

4.1 An illustration: Task specialization by occupation

Figures 3A and 3B show the different task intensity of 2-digit occupations that employ low-educated individuals. Examples of the main tasks conducted on-the-job are also provided in the Appendix Table A1. Note that in that Table all tasks are frequency-adjusted and 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.

Consider 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 tasks, 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 that ranking. Personal care workers elaborate budgets, read diagrams or use calculators with an intensity that is half the sample 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 reading tasks.

At the opposite extreme of the spectrum are sales workers (occupation number 52) an occupation that also 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 0.086 (i.e., they 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. For example, 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 3A provides a visual test of the variation that identifies the parameter of interest α_2. We compute the (frequency unweighted) relative basic 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 working in occupations specialized in math-oriented tasks perform relatively better in the numeracy test than in the literacy one. The upper panel of Figure 3B conducts similar exercises by plotting the average difference between the numeracy and the problem-solving score math in each two-digit occupation against the relative specialization in numeric vs ICT tasks in that occupation. The lower panel plots the relative literacy score (vs problem-solving) against the specialization in reading (vs ICT) tasks. The results are very similar to those in Figure 3B and suggest that, among respondents with basic schooling there is a positive relationship between task specialization in one domain and relative performance in the skill most related to that domain.

4.2 Regression analysis

Table 2 implements a version of Model (2) on a pooled sample of the 15 countries conducting the three assessments (columns 1-9) and on the full sample (columns 10-12). The numeracy, literacy and problem-solving scores are normalized by the country-specific standard deviation. The first set of regressions uses a sample of workers with at most 10 years of potential working experience, the second set uses workers with more than 10 years of working experience and finally the full sample of workers (between 16 and 55 years of age). Table 2 does not distinguish between simple and advanced tasks. All models control for a quadratic polynomial of the number of years of potential 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). We also include nine 1-digit occupation dummies, 22 industry dummies and country dummies. 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 -the latter to control for the possible influence of non-cognitive skills.[26]

We start with the sample of workers with a potentially shorter labor market history. The coefficient of $n - l$ in the first row, first column of Table 2 is 0.16, 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% of one standard deviation better in the numeracy test than in the literacy one. 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 5 of Table 2 to that in column 1, row 1, and amounts to 9.9%=(0.16-0.061) of one standard deviation -about 60% of the return for workers with basic schooling.

When we measure the relationship between ICT specialization and problem solving skills, the results for workers with a basic schooling degree are qualitatively similar. Relative to workers in jobs with a similar share of numeric and ICT tasks, those who fully specialize in numeric tasks obtain 24.8% of one standard deviation higher score in the numeracy test than in the problem-solving one -see column 2, row 2 of Table 2. Finally, basic schooling workers in jobs intensive in reading tasks (and no ICT tasks) obtain in the literacy assessment

[26] All models estimated using the 10 imputed grades in PIAAC, and standard errors are adjusted by that multiple imputation.

an score 33.6% of one standard deviation higher than in the problem solving assessment -see column 3, row 3 of Table 2.

In sum, the estimates across columns 1, 2 and 3 (rows 1, 2 and 3, respectively) suggest that specialization in one type of tasks (say, numeric) increases scores in the skill domain related to that type of tasks relative to the other two.

Secondly, task specialization results in lower differences in the relative score among workers with either a high school or a college degree. For example, among workers with a high school degree, those who fully specialize in numeric tasks (as opposed to ICT ones) obtain a score in the numeracy assessment that is 11.6% of one standard deviation higher than that in the problem solving one (.116 is the difference between the 0.248 estimate in Table 2, row 2, column 2 and the 0.132 estimate in Table 2, row 6, column 2). The estimate is half that estimated among workers with basic education (0.248 percent of one standard deviation).

Heterogeneity by potential experience. We compare the previous results to those in the sample of respondents with more than 10 years of working experience in 2012. The link between specialization in numerical tasks and the relative score in the numerical test is slightly larger for workers at the beginning of the working experience life with basic schooling: full specialization in numeracy tasks (as opposed to reading ones) increases the relative numeracy score by 16.0% of one standard deviation for workers with at most 10 years of work experience (Table 2, column 1, row 1) and 11.3% of one standard deviation in the sample for more than 10 years of working experience (Table 2, column 5, row 1). However, the differences across assessments numeracy relative to problem solving and literacy vs problem solving do not vary much with potential experience.[27]

Magnitude of the impact. To get a grasp of the magnitude of the impacts, we consider how much of the difference in scores across assessments is explained by the specialization in numeracy tasks (relative to reading tasks) of sales workers (an occupation intensive in numeric tasks) vs personal care workers (an occupation intensive in reading tasks). According to the frequency-unadjusted measure of specialization, the difference in specialization in numeracy (as opposed to reading) tasks between both groups is about 34.6% (not shown, see Table A1 for the frequency-adjusted tasks).[28] The estimate implies that the 34.6% specialization in numeric tasks increases the score in the numeracy assessment by 0.16*0.346=5.5% of one standard deviation, relative to the literacy

[27] Although not the topic of this study, the numeracy vs literacy results suggest that the possible skill deterioration documented in previous papers could be explained by differences in the type of numeric vs reading tasks conducted on the job over the life cycle.

[28] Personal care workers conduct on average 3.2 out of 5 reading tasks (they are more likely to read guides or emails) while salespersons conduct 1.8 out of 5 only. On the other hand sales persons conduct 4.9 out of 7 basic numeric tasks, while personal care workers conduct 4.1 out of 7. The difference in specialization at the occupation level is then 34% (=3.2/5-1.8/5) - (4.1/7-4.9/7)

one.

Adjusting by task intensity. The results in Table 2 do not distinguish if a task is conducted at least once a month or every day, so we examine the robustness of the results by constructing 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 3, row 1, column 1 indicate that respondents with less than 10 years of working experience who fully specialize in numerical tasks by conducting all numerical tasks on their jobs every day score 15.4 percent of one standard deviation higher in the numeracy than in the literacy score. Within the group of workers with potential experience below 10 years, the impact of (frequency adjusted) task specialization on differential performance across assessments is very similar across domains. Workers in jobs that devote all of their time to numeric (as opposed to ICT) tasks attain 21.7% of one standard deviation higher score in the numeracy assessment than in the problem solving one -close to the 15.4% in row 1, column 1 of Table 3.

However, the link between frequency-adjusted specialization in numerical tasks and the relative performance in the numeracy vs the literacy test is slightly lower among respondents with a high school degree (9.9% of one standard deviation, obtained by subtracting the 0.061 estimate in row 4, column 1 in Table 2 from the 0.16 estimate in row 1, column 1, Table 2).

Overall, the results in Tables 2 and 3 are consistent with the notion that, for workers with compulsory schooling at most, conducting tasks on the job increases the skills related to that task. On the other hand, the link between specializing in a job on a task and skills in competences related to those tasks the results are somewhat weaker among respondents with either a high school or a college degree.

5 Simple vs advanced tasks

This section explores the role of task complexity in accounting for the relationship between tasks on the job and the measures of cognitive ability in Tables 2 and 3. As mentioned above, low-skilled workers conduct mainly simple tasks, so those are likely to drive the relationship with cognitive skills. Furthermore, under assumptions 2 and 3, for workers with higher levels of schooling, the link may be informative about the degree of selection. But prior to that, we examine the relationship between conducting simple tasks on the job and score in cognitive assessments using specifications in levels.

5.1 The impact of tasks on the job on score levels

Identifying assumption 1 stated that numerical tasks have a similar impact on the numerical part of the test as reading (ICT) task have on the literacy (problem solving) score. One possible way to illustrate that assumption is to conduct level regressions of the score levels on each of the three scores (numeracy, literacy and problem-solving) on the amount of tasks-on-the job related to that assessment (i.e., estimate Model 1 without including fixed effects to proxy for the generic component of skills $C_{0,i}$). Those regressions would support Assumption 1 to the extent that the coefficient of numeric tasks on the numeracy score were similar to that of the reading tasks on literacy. In addition, level regressions are informative about whether our measures of tasks correlate with the level of scores and thus have informational content.

Table 4 shows that numeracy scores among workers with primary education who perform all basic numerical tasks at least once a month are 16.1 percent of one standard deviation higher than among workers who do none of those (see row 1 in Table 4). Similarly, literacy scores among workers with primary education who do all basic reading tasks at their jobs are 18.7 percent of one standard deviation higher than among workers who perform none (see column 2 in Table 4). Furthermore, the similarity of the coefficients (16.1 vs 18.7) lends support to Assumption 1 (reading tasks have a similar impact on literacy scores than numeracy tasks on numeracy scores). However, returns to ICT tasks are higher than numeracy and literacy ones. Problem solving scores are 54.2 percent of one standard deviation higher among workers with primary education who do all basic ICT tasks at their jobs (see Table 4, column 3, row 3).The magnitude triples those in rows 1 or 2.[29]

Overall, our summary from Table 4 is that our measures of simple tasks conducted on the job correlate with the related assessment in PIAAC. The estimated magnitude $\alpha_{2,m}$ is similar in the numeracy and literacy parts ($m = n, l$) but it is larger in the problem-solving case ($m = p$). Hence, in what follows, to establish the validity of Assumption 1 in each particular case, we rely on whether individual fixed-effect estimates (i.e., Model (2)) differ depending on the particular pair of domains analyzed.

The differential skill return to specialization in basic tasks. Tables 5a, 5b and

[29] Skill returns to performing basic tasks are lower for individuals with high school or college degree. One college individual would only score 7.5 percent of one standard deviation higher if performing basic numeracy tasks on the job (see Table 4, column 1, row 7). However, when performing advanced numeracy tasks, the numeracy score in the exam would be a 28 percent of one standard deviation higher (see Table 4, column 1, rows 10 and 16). This is also what happens when we analyze literacy and ICT tasks. Furthermore, according to the estimates in Table 4, respondents with primary schooling obtain a very high return of doing advanced tasks: their numeracy, literacy or problem solving score increases by respectively 23, 12 or 39.2 percent of one standard deviation from advanced numeracy (reading) tasks.

5c introduce individual fixed-effects to examine the relation between specialization in a set of *basic* tasks on the job and differential cognitive skills related to that domain. The results imply that respondents without either a high school or a college degree who fully specialize in basic numerical tasks score 10.5% of one standard deviation higher in the numeracy assessment than workers who are equally specialized in numeric and reading tasks (Table 5a, first column, first row). When we measure the impact of specialization in numeracy vs ICT tasks on numeracy scores (relative to problem-solving), the impact is somewhat smaller: 2.8% of one standard deviation, but it is imprecisely estimated. Finally, workers with basic schooling who specialize in reading vs ICT tasks obtain a higher score in the reading score than in the problem solving score (9.8% of one standard deviation, close to the 10.5% estimate in Table 5, column 1, row 1). The estimate of the impact of specialization in basic tasks on relative scores varies then between 2.8 and 10.5% among workers with primary schooling, but taking into account standard errors, we cannot reject the hypothesis that the three estimates presented in Table 5 are equal in size.

To gain precision, column 4 in Table 5a stacks all the previous regressions. That is, each individual contributes three observations: one for each pair of assessments. The coefficient of each pair of tasks on their correspondent assessments are constrained to be the same, and standard errors are clustered at the individual level to take into account that observations from the same individual may be correlated. The coefficient in Table 5, column 4, row 4 is 0.108. This suggests that low-skill workers in jobs that specialize in one domain of basic tasks (for example, reading vs ICT) obtain a 10.8% of one standard deviation higher score in the related assessment (for example, literacy) than in the rest (for example, problem solving).

Tables 5b and 5b present the comparable estimate on respondents with more than 10 years of working experience and on the full sample, respectively. Among workers with more than 10 years of potential experience, the impact of specialization on a set of basic tasks increases scores in the most related assessment by 5.9% of one standard deviation (Table 5b, row 4, column 4). For the full sample the estimated impact is 8.9% (Table 5c, row 4, column 4). In sum, specializing on a set of basic tasks increases cognitive skills related to those tasks more for workers with basic schooling and less than 10 years of experience.[30]

[30] Comparing the coefficients in Table 4 (estimations in models that do not control for worker-level fixed effects) and Table 5 (that do include worker-specific fixed effects) for the full sample of respondents suggests that individual heterogeneity is an important determinant of the task content of a job and of cognitive skills. The coefficients when we control for individual fixed effects indicate that full specialization in basic numerical tasks increase (differential) numeracy scores by 10.5 percent of one standard deviation, while cross-section regressions suggest effects between 16.1 percent in numeracy scores). Secondly, specialization in advanced numerical tasks increases (differential) numeracy scores by 0,6 percent of one standard deviation, while the estimate when we just compare absolute use of numerical skills is larger (23 to 12 percent of one standard deviation, Table 4, row 10 and row 11, both in numeracy and literacy).

Impacts by school level. Next, we compare the impact of conducting basic tasks on the job on groups with higher educational levels. In practice, we subtract the estimate for respondents with high school from that for respondents with basic school, yielding the impact of specialization in basic tasks on the relative performance in the corresponding test for respondents with high school. We do this exercise using the estimates in Table 5a, and using the sample where respondents have had less time to sort (individuals with less than 10 years of working experience). The impact of basic tasks on cognitive skills is smaller for high school graduates than for workers with basic schooling. When we measure specialization in basic tasks using the three measures as a benchmark (fourth column of table 5a, replicating difference in scores) the impact of among high school graduates is 3.8% (0.038=0.108-0.070), subtracting the estimate in row 8, column 4, from that in row 4, column 4, in Table 5a.

Overall, although point estimates vary with the definition of specialization, Table 5a suggests that the cognitive skill returns to specializing in basic tasks for workers with either high school or college degree are between non-significant and 40% of those we find among respondents with basic schooling. The result is consistent with the notion that learning through basic tasks on the job increases the skills of respondents with basic schooling.

6 Subsample analysis and magnitude of the estimates

Thus far, we have documented that individuals with primary education working in jobs that are intensive in basic math (relative to reading or ICT) tasks score between 7 and 19 percent of one standard deviation higher scores in numeracy tests (relative to their performance in literacy tests) skills. Those impacts are smaller among groups with higher education levels, specially when we examine cohorts that have not had much time to sort in the labour market. As it was discussed in Section 2, those estimates could partially reflect the impact of workers with a better initial endowment sorting to jobs akin to their abilities. This Section uses alternative ways to gauge the impact of sorting.

6.1 Gender

We analyze in Table 6 separate impacts by gender[31]. To achieve precision, we proceed as in Table 5 column 4 and stack the three measures for each individual (the three pairwise differences between numeracy, literacy and problem solving scores) and regress them on the corresponding pairwise difference in the associated tasks. As in the previous case, we discuss first the case of workers with less than 10 years of potential experience and the result for the full sample. Interestingly, the patterns we detect in Table 5 are more pronounced for females than for males.

Firstly, among low-skill men, those who specialize in basic tasks obtain a relative score in that domain 7% of one standard deviation higher than low-skill males in jobs with an even distribution of tasks. The standard error is 5% of one standard deviation, so the estimate is not significantly different from zero. The corresponding estimate for low-skill females is twice as large: 14.7% of one standard deviation (standard error: 4.8%).

Secondly, and as it was the case in Table 5, the response of differential scores to the variation in specializing in basic tasks is stronger for low-skill females than for women with a high school or a college degree. Among females with a high school degree, those who work in jobs where they fully specialize in a basic task (say, numeric) obtain a score in that domain (numeracy) 2.9% higher than females in jobs with a balanced set of tasks. The estimate is five times smaller that of low skill females.

We note that the finding that the relationship between task specialization and scores is stronger for low-skill females than for low-skill males suggest that all our results cannot be entirely driven by sorting. Men tend to accumulate more working experience in the labor market. Hence, they might be more exposed to selection.

6.2 Industry

A second possibility examines the skill return to basic tasks by industries. Table 7 shows the impacts of task specialization on differential scores in selected industries -we basically chose those industries with more than 10,000 individuals in the sample. Industries vary in the fraction of males working in the industry (manufacturing and construction being typically male-dominated industries) but also in their task content. According to PIAAC, Manufacturing,

[31] Gender significant differences in the skill use have also been observed using PIAAC data. Pető and Reizer (2020) show that women use cognitive skills in a 0.3 of one standard deviation less than men, and this difference is even higher in numeracy with respect to literacy or ICT skill use (note that they name "cognitive skill use" what we name "tasks"). These authors estimate the impact of the gender on skill use whereas in our paper we estimate the impact of task specialization on differential cognitive scores

Construction and Retail are industries more intensive in numerical tasks, while Teaching and Social Services are more intensive in reading ones. Hence, we explore whether the relationship between task specialization and cognitive skills happens within industries. To obtain precise estimates, we pool the data across all pairs of assessments.

The estimates in the first row of Table 7 suggest that, for workers without any high school or college degree, the link between specialization in a particular set of basic tasks and performance in the related cognitive skill is similar across industries. The estimate of fully specializing in a set of tasks (say, numeric) on the related cognitive scores range between around 9% to12% of one standard deviation higher score in manufacturing retail or construction (Table 7, row 1, columns 1 to 3) and the 18.5% in social services and health (columns 4 and 5). The exception is the teaching industry, where the estimates are not different from zero and the sample size is small.

On the contrary, the cognitive skill returns to task specialization is lower among workers with either a high school or college degree. Those individuals range from less than 1% of one-standard deviation in manufacturing (Table 7, row 3 column 2) to about 11.5% and 9.2% of one standard deviation in social services and health or retail (row 3, columns 3 and 5).

In sum, basic tasks have a similar impact on cognitive skills of low-skilled workers, while that impact is fragile for workers with a college or a high school degree. An interpretation is that the impact of basic tasks for the latter groups indicates not human capital acquisition, but possibly selection.

6.3 The magnitude of the estimates

Estimates for the full sample. We start with the impact of full specialization on simple numerical tasks on the relative numeracy score as implied by the results in Table 5c and Table 3. In the overall 16-55 sample, the estimate of full specialization in basic numerical tasks on the relative performance in the numeracy test ($\hat{\alpha}_{2,basic}$) is 7.1% of one standard deviation (column 1, row 1 in Table 5c). Respondents with a high school degree who specialize in simple numeracy tasks in their jobs increase their relative performance in the numeracy test by 1.4% of one standard deviation -which, under assumptions 2 and 3, could reflect sorting (i.e. $\hat{\alpha}_{2,highschool} = 0.014$). The net impact of task specialization on the relative numerical score is the difference between both estimates $\hat{\alpha}_{2,basic} - \hat{\alpha}_{2,highschool}$, which is 5.7% of one standard deviation, (0.057=0.071-0.014).

Estimates for the individuals less experienced. The estimates become larger when we focus on the low working experience sample. This sample is specially interesting as workers with 10 or less than 10 years of potential experience have had less time to select into jobs more akin to their characteristics. The raw estimate of full specialization on the relative performance in the numeracy test among basic schooling respondents is 10.8% of one standard deviation (shown in the fourth row of column 4 in Table 5a).

For respondents with a high school degree, the impact of specialization in basic tasks is 3.8% (obtained by subtracting the 0.07 differential impact among respondents with a high school degree in column 4, row 8, in Table 5a from the main impact of 10.8 in column 4, row 4). The return to specialization in basic tasks on their jobs for respondents with a college degree is 2.8% of one standard deviation (obtained by subtracting the 0.078 impact in column 4, row 12, in Table 5a from the main impact of 10.8).

Hence, under the assumption that the return to specializing in basic tasks for respondents with a high school or college degree basically measures sorting, we can apply equation (1) obtaining that workers with basic schooling who fully specialize in a set of basic tasks on a job perform around a 7% of one standard deviation better on the assessment relative to a worker with a balanced set of tasks.

6.4 Evidence from synthetic cohorts

An alternative way of controlling for possible selection biases examines how cohort-level changes in the reading content of jobs relate to cohort level changes in literacy. As mentioned above, cohort-level changes in the reading content of a job are unlikely the result of individual sorting across jobs. We define cohorts by year of birth, gender, level of education and country. We focus on two groups of birth years: 1950-1959 and 1960-1969. Both cohorts are observed in both assessments during their working lives and, as Figure 2 showed, there is a substantial degree of cross-country and cross-cohort heterogeneity in their exposure to reading tasks during the period considered. To increase the degree of variation in the data, we aggregate the use of reading tasks taking into account the reported frequency of each of the tasks. The sample contains 50 cells of about 150 individuals in each of them (on average).

The first row in Panel A of Table 8 shows that, among respondents with basic education, an increase of 100% in the use of reading tasks on the job (at the cohort level) increases scores in the financial literacy assessment by 1.2 standard deviations (standard error: 0.47 percent of one standard deviation).

Column 2 in Table 8 examines the role of omitted variables by including in the regression the cohort-level change in *numeric* tasks. That variable should have little explanatory power (in principle, preparing budgets may not increase literacy directly), but may pick up any spurious trend affecting both the tasks on the job and the change in literacy skills. The evidence in Table 8 suggests that our measure of reading tasks is not picking up a general trend towards more task-intensive jobs. Columns 3 and 4 demand more from the data by introducing country-level dummies in the regression. That specification identifies changes in the reading task content across gender and year of birth groups within countries. The estimates in columns 3 and 4 of Table 7 imply that workers with primary schooling who increased their time to reading- or writing- related tasks on the job over the period increased their literacy scores by between 72 (Table 8, first row, column 4) and 84 percent of one standard deviation (Table 8, first row, column 3). Dividing by 18 years of experience results in an estimate of 70/18=3.89 percent of one standard deviation per year.

We can compare those estimates to those in the Table 5A, row 4, column 4, that are about 10.8 percent. The average actual experience of individuals with 10 years of experience at most is 4.8 years. Hence the fixed-effect estimate suggests about = 2.25 (=10.8/4.8) percent of one standard deviation per year. While the synthetic cohort is larger than the worker-fixed effect one, both estimates are not incompatible -specially if one takes into account that we do not know in PIAAC during how long were reading tasks acquired on the job.

Interestingly, the results of the impact of the increase in reading tasks on the change in literacy scores for high-school and college groups are weak and rather fragile. For example, once we introduce country fixed-effects, we cannot rule out that the increase in basic reading tasks does not affect literacy scores among those groups.

Overall, the evidence from the synthetic cohort analysis is broadly consistent with the one found in PIAAC. We find this remarkable, given the very different set of assumptions involved in each procedure.

6.5 Assessing the magnitude of the estimates

Overall, the results are consistent with the hypothesis that on-the-job learning may substitute formal schooling for unskilled young workers. However, that is a qualitative assessment. We conduct now some back of the envelope calculations comparing our estimates to existing work analyzing how cognitive skills vary with formal education.

Our estimates suggest that specializing in numerical tasks increases the differential numerical score of individuals with basic education by about 10.8% of one standard deviation (Table 5, row 4 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 7.8% of one standard deviation, as described above.

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 other tasks in their current job only or during their complete working lives. Hence, we make the assumption that workers conducted numerical or literacy tasks during 4.8 years of experience, i.e. the average number of years worked among respondents with less than 10 years of potential experience. That conservative assumption implies that one year of experience increases numeracy skills by between 1.46% (=7/4.8) and 2.25% (=10.8/4.8) of one standard deviation.

A caveat is that less than half of the workers with basic schooling conduct basic tasks (see Figure 1). Assuming that 30% of workers with basic schooling conduct basic tasks on their jobs, the estimate of the impact of one year of experience on numeracy skills would be between 0.44% (=1.46*0.3) and 0.75%(=2.25*0.3) of one standard deviation.

To provide some sort of a benchmark, Hanushek et al. (2015) estimate that, in the United States, increasing compulsory education by one year increases skills by between 2.7% and 2.9% of one standard deviation. Hence, one extra year of schooling would be equivalent to between 1.3 (=2.9/2.25) and 2 years (=2.9/1.46) of on-the-job learning. If one takes into account that not all workers with basic schooling may end up in a job with basic education, one extra year of schooling would be equivalent to between 3.9 (=2.9/0.75) and 5.2 (=2.9/0.44) years of experience.

7 Conclusions

Cognitive 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, literacy and problem-solving skills in eighteen OECD countries that implemented the PIAAC survey, focusing on individuals with low levels of schooling.

We use two empirical strategies. Firstly, we control for individual fixed effects by analyzing how the relative performance in numeracy, literacy and problem solving assessment vary with the differential exposure to numeracy, literacy and problem-solving tasks on-the-job. Our preferred estimates suggest that, among individuals with at most compulsory schooling, full specialization in basic numerical tasks increases the relative numeracy score by between 7 and 11 percent of one standard deviation. A second strategy uses repeated cross-sections of cognitive assessments to study how cohort-level changes in the reading content of jobs correlate with literacy scores. An interpretation of our results is 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 between half and a fourth 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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Figure 1: Percentage of individuals performing basic tasks by country and level of education

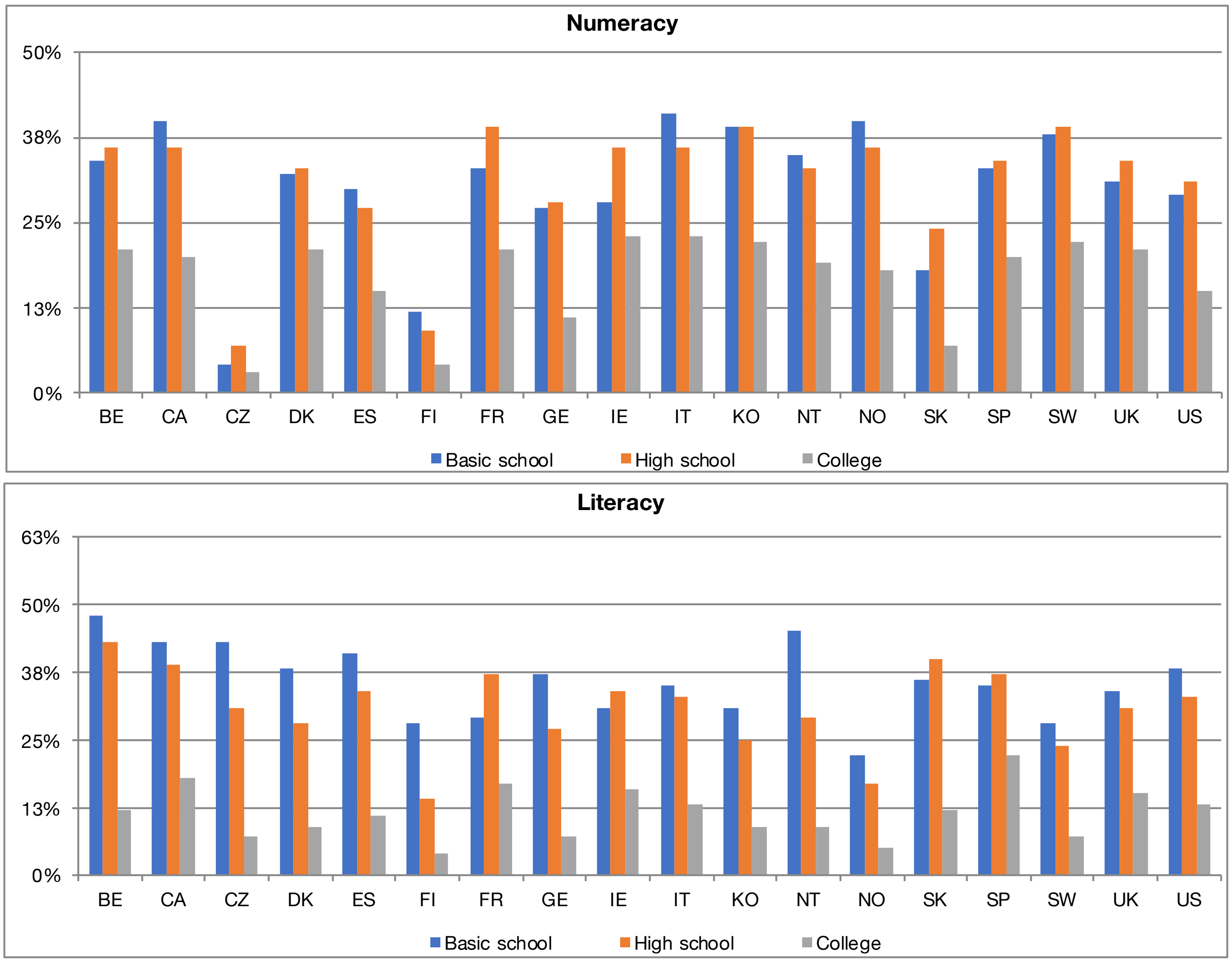
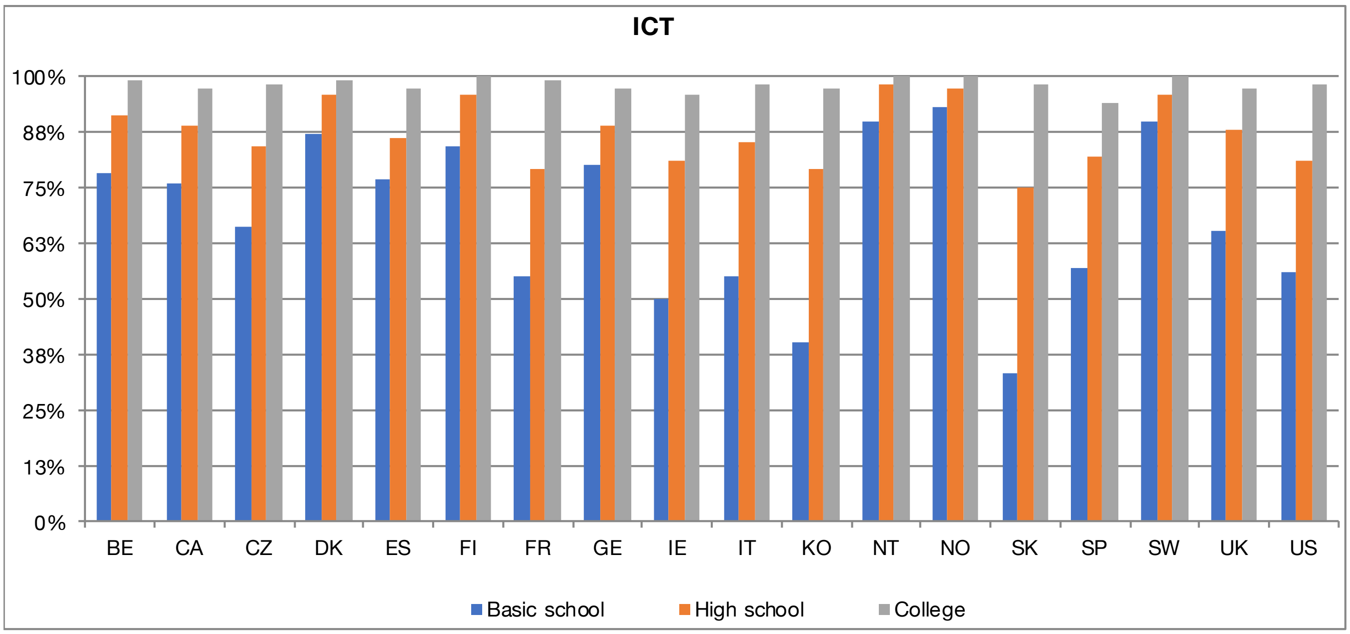


Figure 1 (cont.): Percentage of individuals performing basic tasks by country and level of education



Source: PIAAC (2012).

Sample of respondents of 16-55 years of age. The figure shows the percentage of individuals of the sample performing at least once a month a basic numeracy, literacy or ICT task according to their country and level of education. Basic numeracy tasks are elaborate budgets, use calculator, use fractions, read diagrams and bills. Basic literacy tasks are read emails, guides, manuals and articles and write emails and reports. Basic ICT tasks are using email or internet and processing texts and conducting transactions. The classification of tasks is based following Principal Component Analysis reported on Table A1.

Figure 2: Fraction of time using reading tasks over the life cycle, evidence from IALS and PIAAC

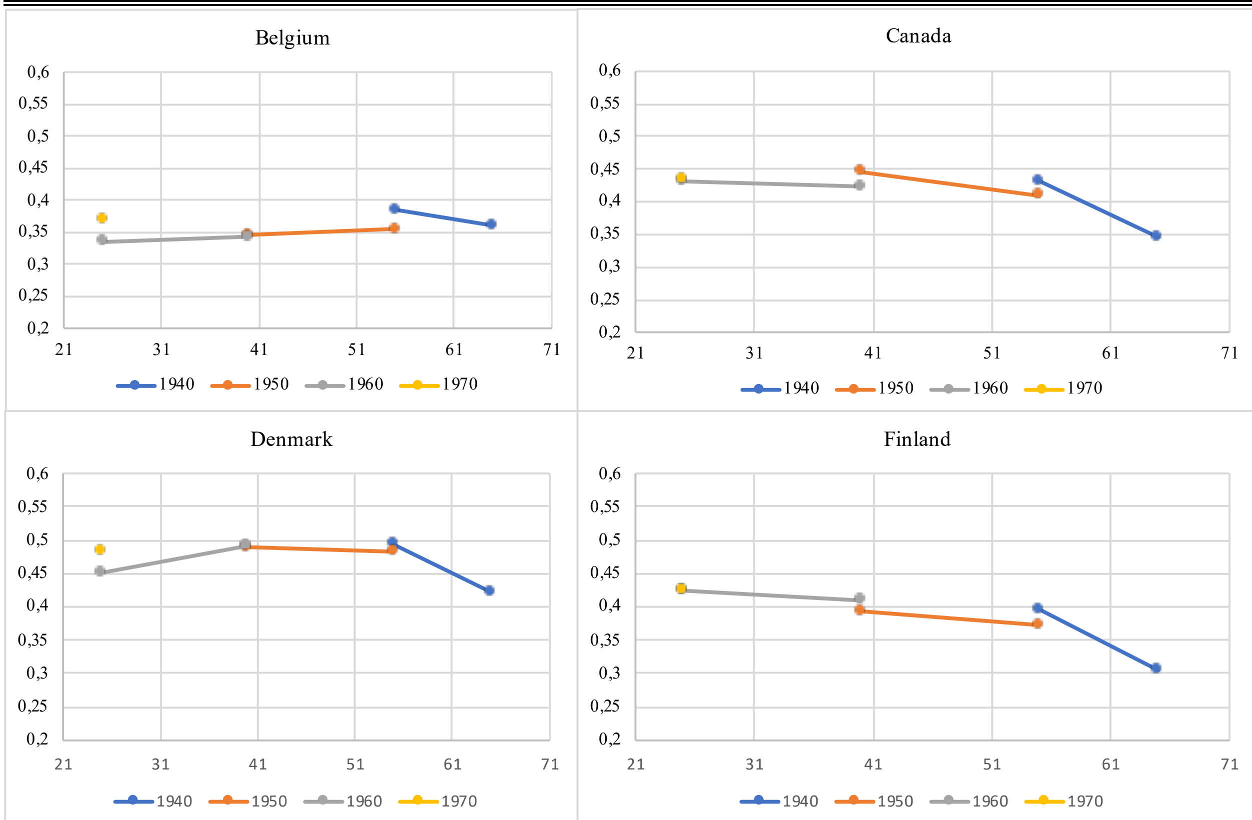


Figure 2 (cont.): Fraction of time using reading tasks over the life cycle, evidence from IALS and PIAAC

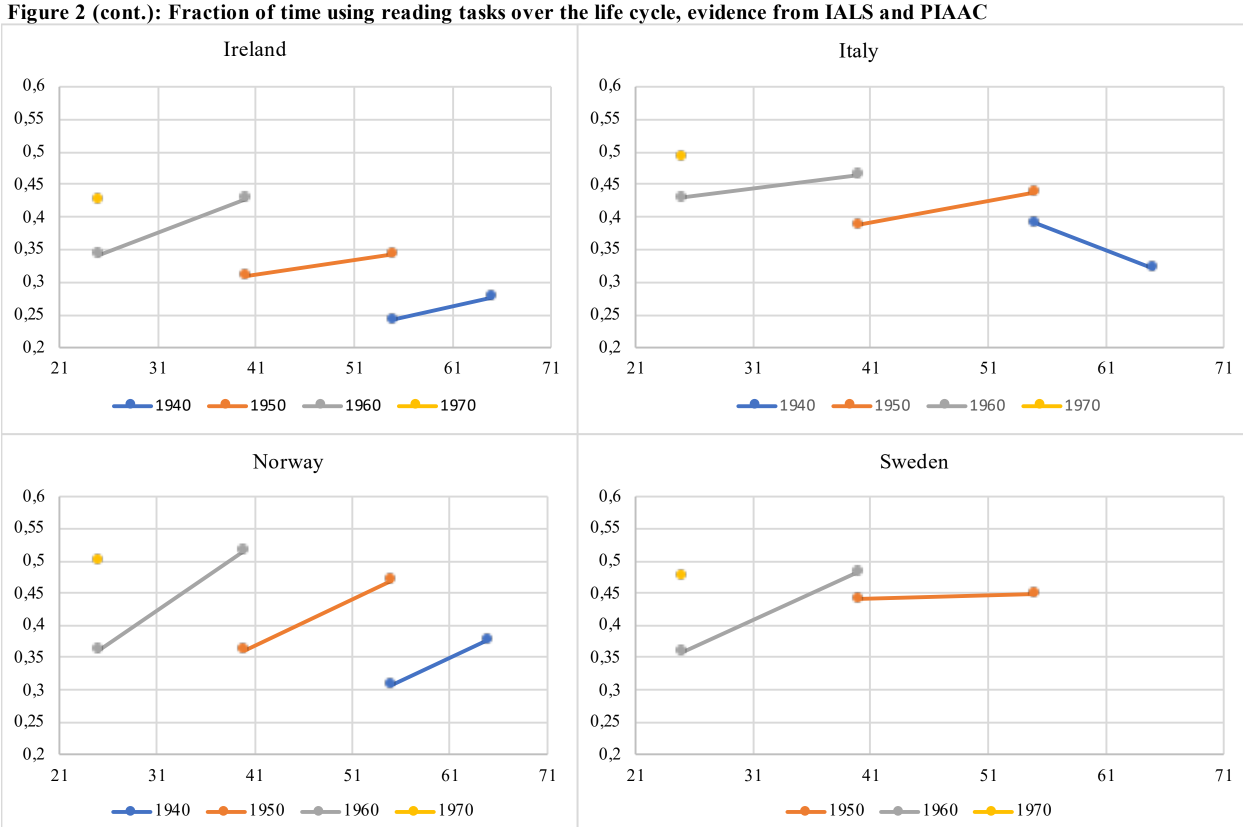
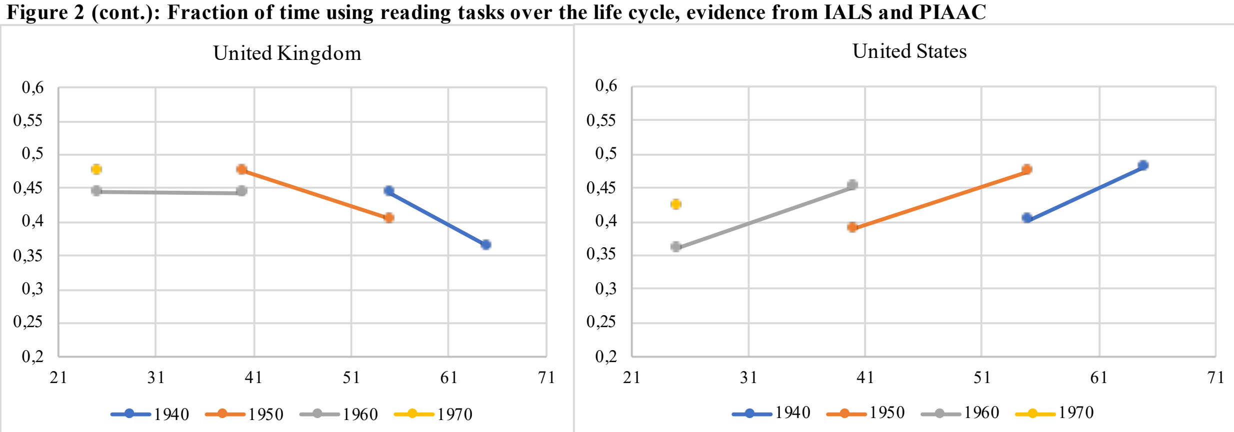


Figure 2 (cont.): Fraction of time using reading tasks over the life cycle, evidence from IALS and PIAAC



Source: combined IALS (1994) and PIAAC (2012) samples of workers without a college degree. IALS asks respondents who worked in the last 12 months if they read letters or memos, reports, articles or manuals, wrote letters and reports or articles. We select a similar sample of individuals working in the last 12 months in PIAAC.

The Figure includes cohorts born between 1940 and 1979, as they would still be below 65 years of age eighteen years at the time of the PIAAC assessment (2012). We aggregate observations in cells defined by 10-year birth cohorts,schooling level, gender and country. We assign the IALS and PIAAC measurements of the 1940-1947 cohort to 55 and 65, respectively (shown for completeness, not used in regresssions). We assign to the 1950-1959 cohort the ages of 40 and 55, respectively. We assign the ages to the 1960-1969 cohort to 25 years in PIAAC (the average would be 30) and 55 in IALS (the average age would be 47). The 1970-1979 cohort is available in PIAAC only.

Figure 3.A: Relative specialization in numeric tasks vs differential performance in the numeracy, literacy and problem-solving tests

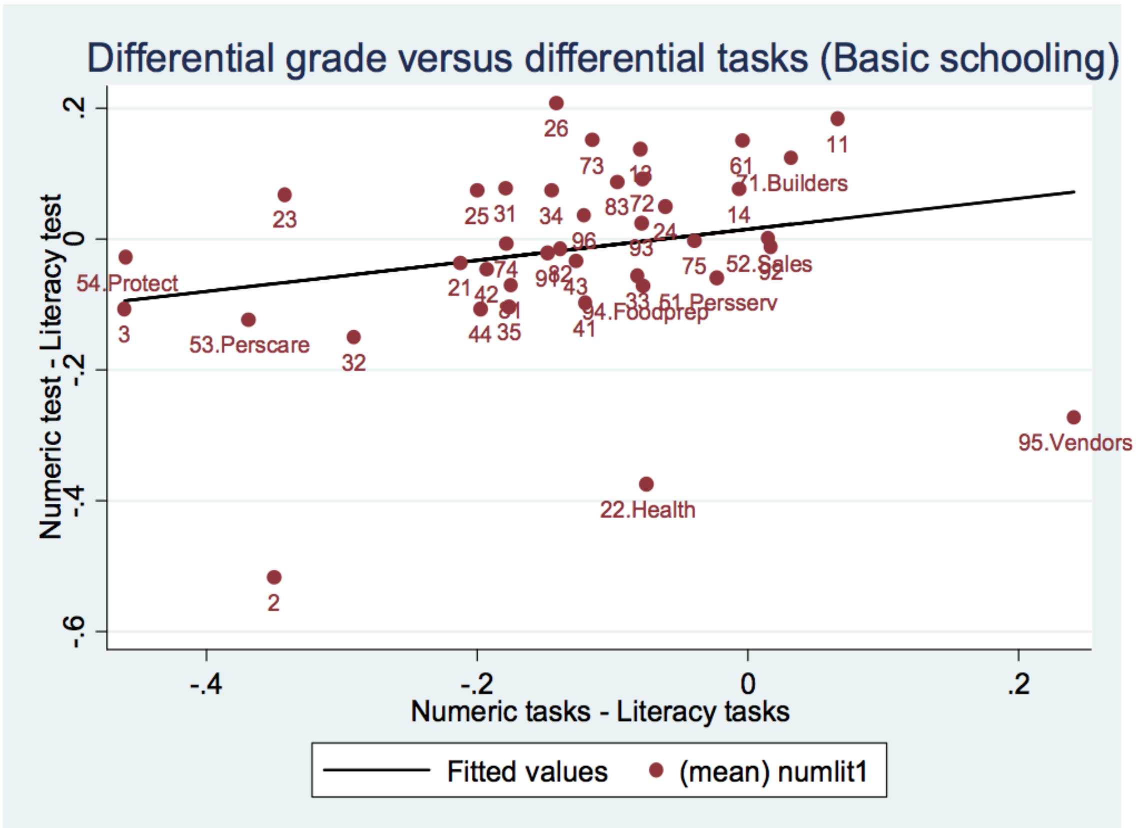
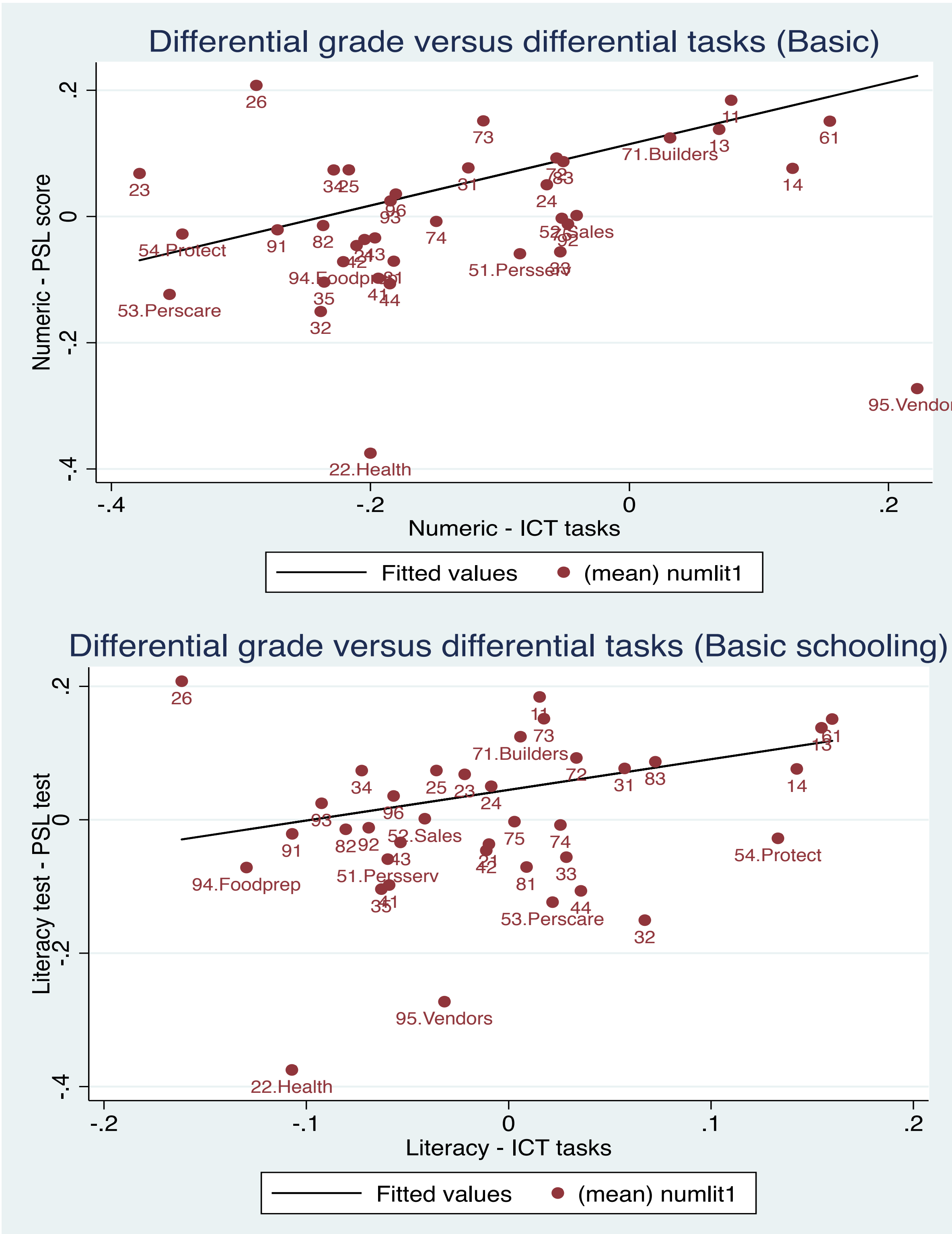


Figure 3B: Relative specialization in numeric tasks vs differential performance in the numeracy, literacy and problem-solving tests



Source: PIAAC (2012). Sample of respondents with at most compulsory schooling.

The horizontal axis of Figure 3A shows, for each 2-digit occupation available in PIAAC, the average specialization in basic numeric tasks relative to reading ones (frequency unadjusted).

The vertical axis of Figure 3A shows the average individual differences in standardized scores between the numeracy and literacy assessments. A positive relationship suggests a higher relative score in the numeracy score (relative to the literacy one) for occupations intensive in basic numeric tasks (compared to reading).

Figure 3B shows the equivalent for numeracy minus problem solving and for literacy versus problem solving.

Table 1: Summary statistics, by country

		Belgium	Canada	Czech Rep.	Denmark	Estonia	Finland	France	Germany	Ireland
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Working experience (mean)		16,5	15,6	15,1	17,4	14,7	14,5	14,6	16,3	14,3
Male (%)		51	46	45	51	46	51	50	50	45
Primary school (%)		12	15	6	18	13	8	2	12	17
Secondary (%)		47	40	70	38	46	60	56	54	40
Tertiary education (%)		42	44	25	44	41	32	42	34	43
Numeracy test (mean)	Primary	245.78	213.49	234.41	236.41	241.96	261.58	181.43	224.49	225.31
	Secondary	275.66	256.92	273	275.81	268.45	284.72	243.99	271.19	257.42
	Tertiary	313.49	285.27	308.98	302.54	292.15	320.54	297.43	306.48	287.42
Reading test (mean)	Primary	243.69	223.86	243.31	232.09	249.25	261.15	201.66	231.38	237.94
	Secondary	269.04	266.32	272.36	265.13	269.76	290.05	253.76	268.47	268.08
	Tertiary	307.34	291.64	307	292.51	292.92	327.14	295.61	299.50	293.37
Problem solving test (mean)	Primary	246.32	238.27	255.54	257.14	245.62	267.79		255.09	236.96
	Secondary	270.30	238.28	275.77	275.68	263.94	285.55		276.99	269.82
	Tertiary	300.20	238.29	303.48	300.69	285.16	314.78		301.90	291.85
Sample size		3211	19566	3499	3918	4891	3249	4379	3676	4118

		Italy	Korea	Netherlands	Norway	Slovak Rep.	Spain	Sweden	UK (*)	United States
		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Working experience (mean)		14,0	11,3	15,7	15,3	14,3	13,9	14,9	15,4	16,7
Male (%)		53	49	49	53	50	50	51	42	47
Primary school (%)		29	9	24	17	11	43	9	22	9
Secondary (%)		51	40	41	39	68	21	51	37	50
Tertiary education (%)		20	51	35	43	21	36	40	41	42
Numeracy test (mean)	Primary	235.16	228.12	254	252.94	240.08	227.69	235.02	230.11	205.22
	Secondary	267.15	256.72	287.67	279.38	279.66	255.09	277.88	260.75	244.33
	Tertiary	284.14	284.85	312.26	310.50	306.81	279.45	311.02	289.42	290.16
Reading test (mean)	Primary	238.26	242.05	257.96	260.00	247.72	234.91	238.77	245.53	228.11
	Secondary	265.07	265.99	290.34	277.81	276.98	257.78	279.12	273.31	261.73
	Tertiary	283.93	292.11	315.08	306.41	296.62	283.92	309.54	298.72	301.37
Problem solving test (mean)	Primary		242.26	262.02	265.28	256.24		251.87	251.73	234.49
	Secondary		265.75	286.98	280.26	272.83		286.42	272.81	265.00
	Tertiary		288.24	308.36	306.16	295.15		312.16	294.20	298.35
Sample size		2911	4293	3296	3260	3479	3917	2737	6159	3252

(*) The UK sample pools together England and Northern Ireland. PIAAC wave 1, respondents between 16 and 55 years of age. Statistics unweighted. The sample contains individuals who are working or report having worked in the last 12 months. The scale of the test is between 0 and 500, and the standard deviation is about 50 in each country.

Table 2: The impact of task specialization on relative performance in numeracy and literacy score

	Sample of 15 countries conducting the three assessments									Full sample of countries		
	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score	Math score - Literacy score	Math score - Literacy score	Math score - Literacy score
	<=10 years of working experience			>10 years of working experience			16-55 years of age			<=10 years of working	>10 years of working	16-55 years of age
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. (Numeracy-Literacy tasks)	0.160***	--	--	0.113***	--	--	0.128***	--	--	0.156***	0.117***	0.129***
	(0.035)			(0.022)			(0.018)			(0.033)	(0.020)	(0.017)
2. (Numeracy - ICT tasks)	--	0.248***	--	--	0.263***	--	--	0.250***	--			
		(0.045)			(0.031)			(0.027)		--	--	--
3. (Reading - ICT tasks)	--	--	0.336***	--	--	0.272***	--	--	0.286***			
			(0.046)			(0.025)			(0.026)			
4. (Numeracy-Literacy tasks)*High school	-0.061*	--	--	-0.015	--	--	-0.031*	--	--	-0.056*	-0.019	-0.031*
	(0.036)			(0.022)			(0.019)			(0.033)	(0.021)	(0.017)
5. (Numeracy - ICT tasks)*High school	--	-0.132***	--	--	-0.052*	--		-0.072**	--			
		(0.038)			(0.031)		--	(0.026)		--	--	--
6. (Reading - ICT tasks)*High school	--	--	-0.185***	--	--	-0.109***			-0.128***			
			(0.042)			(0.023)			(0.024)			
7. (Numeracy-Literacy tasks)*College	-0.004	--	--	0.009	--	--	0.008	--	--	-0.010	-0.007	0.003
	(0.040)			(0.027)			(0.022)			(0.037)	(0.027)	(0.021)
8. (Numeracy-ICT tasks)*College	--	-0.119***	--	--	-0.088***	--		-0.095***	--			
		(0.045)			(0.032)			(0.027)		--	--	--
9. (Reading-ICT tasks)*College	--	--	-0.182***	--	--	-0.104***	--		-0.112***			
			(0.046)			(0.023)			(0.026)			
Average number of obs.	24,567	22,759	22,759	45,425	36,684	36,684	69,992	59,443	59,443	27,600	53,396	80,996
Average R squared	0.035	0.035	0.035	0.035	0.035	0.035	0.073	0.035	0.0405	0.073	0.073	0.073

Source: PIAAC

Footnotes: a. The dependent variable is the individual-specific pairwise difference between the scores in the numeracy, literacy and problem solving assessments, each normalized by its s.d.

"Numeracy tasks" task is the fraction of all numeracy tasks that the respondents reports having performed in his or her job (current or last). The same definition applies to "Reading" and "ICT" tasks. The difference between two tasks is the degree of specialization in one type of tasks. For example, "numeric - lit" takes value 1 if the individual performs all numeric tasks in his or her job and none of the literacy ones. The difference in sample sizes between column 1, on one hand, and 2 and 3, on the other is that PSL is not available for exams done on paper.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of potential 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). We also include nine 1-digit occupation dummies, 22 industry dummies and country dummies. 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. All specifications consider the set of 10 plausible values (PVs) from PIAAC direct measures of skills in each of the three domains. Standard errors are adjusted by heteroscedasticity and considered multiply-imputed data.

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

Table 3: The impact of task specialization on relative performance in numeracy, literacy and problem solving scores (taking into account task intensity)

Dependent variable:	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score	Math score - Literacy score	Math score - PSL score	Literacy score - PSL score
Sample	<=10 years of working experience			>10 years of working experience			16-55 years of age		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. (Fraction of time numeracy- reading tasks)	0.154**	--	--	0.186***	--	--	0.180***	--	--
	(0.084)			(0.040)			(0.039)		
2. (Fraction of time numeracy - ICT tasks)	--	0.217**	--	--	0.446***	--	--	0.389***	--
		(0.099)			(0.058)			(0.055)	
3. (Fraction of time reading -ICT tasks)	--	--	0.196**	--	--	0.225***	--	--	0.220***
			(0.103)			(0.056)			(0.054)
4. (Fraction of time numeracy- reading tasks)*High school	-0.025	--	--	-0.028	--	--	-0.030	--	--
	(0.092)			(0.047)			(0.043)		
5. (Fraction of time numeracy- ICT tasks)*High school	--	0.037	--	--	-0.063	--	--	-0.049	--
		(0.098)			(0.065)			(0.058)	
6. (Fraction of time reading- ICT tasks)*High school	--	--	-0.002	--	--	-0.005	--		-0.007
			(0.097)			(0.057)			(0.050)
7. (Fraction of time numeracy- reading tasks)*College	0.121	--	--	0.052	--	--	0.071*	--	--
	(0.091)			(0.044)			(0.042)		
7. (Fraction of time numeracy- reading tasks)*College	--	0.010	--	--	-0.093*	--	--	-0.054	--
		(0.010)			(0.054)			(0.055)	
7. (Fraction of time numeracy- reading tasks)*College	--	--	0.043	--	--	0.070	--	--	0.047
			(0.098)			(0.060)			(0.053)
Average number of obs.	24,567	22,784	22,784	45,425	36,714	36,714	69,992	59,498	59,498
Average R squared	0.061	0.0365	0.0289	0.061	0.0365	0.0289	0.062	0.0365	0.0289

Source: PIAAC (Sample 15 countries)

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 reading 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 and none to the reading rasks

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.

Standard errors are adjusted by heteroscedasticity. ***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively.

Table 4: The impact of conducting tasks on scores

Dependent variable:	Numeric	Literacy	Problem solving
	(1)	(2)	(3)
1. (Numeracy tasks)$_{basic}$	0.161*** (0.026)		
2. (Literacy tasks)$_{basic}$		0.187*** (0.032)	
3. (ICT tasks)$_{basic}$			0.542*** (0.043)
4. (Numeracy tasks)$_{basic}$*High school	-0.052* (0.029)		
5. (Literacy tasks)$_{basic}$*High school		-0.007 (0.036)	
6. (ICT tasks)$_{basic}$*High school			-0.077 (0.0492)
7. (Numeracy tasks)$_{basic}$*College	-0.075** (0.032)		
8. (Literacy tasks)$_{basic}$*College		-0.106*** (0.040)	
9. (ICT tasks)$_{basic}$*College			-0.1124* (0.0574)
10. (Numeracy tasks)$_{advanced}$	0.233*** (0.027)		
11. (Literacy tasks)$_{advanced}$		0.120*** (0.025)	
12. (ICT tasks)$_{advanced}$			0.392*** (0.0291)
13. (Numeracy tasks)$_{advanced}$*High school	-0.006 (0.029)		
14. (Literacy tasks)$_{advanced}$*High school		-0.037 (0.026)	
15. (ICT tasks)$_{advanced}$*High school			-0.0487 (0.0304)
16. (Numeracy tasks)$_{advanced}$*College	0.047 (0.031)		
17. (Literacy tasks)$_{advanced}$*College		0.007 (0.030)	
18. (ICT tasks)$_{advanced}$*College			-0.0519*** (0.0327)
Average number of obs.	69,992	69,992	59,498
Average R2	0.290	0.259	0.259

Source: PIAAC - 15 countries

Footnotes: a. The dependent variable is the individual-specific score in the numeracy test, the score in the literacy test and the score in the problem solving test, each normalized by its s.d.

"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, and ICT the fraction of ICT tasks reported.

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). All specifications include individual fixed effects, country, 2-digit occupation and industry dummies. 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

c. All specifications consider the set of 10 plausible values (PVs) from PIAAC direct measures of skills in each of the three domains. Standard errors are adjusted by heteroscedasticity and considered multiply-imputed data.

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

Table 5a: The impact of task specialization on relative numeracy, literacy and problem solving (respondents with 10 or lower than 10 years of working experience)

	Sample of 15 countries conducting the three assessments			
Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
	(1)	(2)	(3)	(4)
1. (Numeracy-Reading tasks)$_{basic}$	0.105**	--	--	--
	(0.048)			
2. (Numeracy-ICT tasks)$_{basic}$	--	0.028	--	--
		(0.060)		
3. (Reading-ICT tasks)$_{basic}$	--	--	0.098*	--
			(0.057)	
4. (Difference in tasks)$_{basic}$	--	--	--	0.108***
				(0.036)
5. (Numeracy-Reading tasks)$_{basic}$*High school	-0.053	--	--	--
	(0.053)			
6. (Numeracy-ICT tasks)$_{basic}$*High school	--	0.010	--	--
		(0.060)		
7. (Reading-ICT tasks)$_{basic}$*High school	--	--	-0.091	--
			(0.063)	
8.(Difference in tasks)$_{basic}$*High school	--	--	--	-0.070*
				(0.038)
9. (Numeracy-Literacy tasks)$_{basic}$*College	-0.030	--	--	--
	(0.052)			
10. (Numeracy-ICT tasks)$_{basic}$*College	--	-0.002	--	--
		(0.064)		
11. (Reading-ICT tasks)$_{basic}$*College	--	--	-0.103*	--
			(0.064)	
12. (Difference in tasks)$_{basic}$*College	--	--	--	-0.078**
				(0.038)
13. (Numeracy-Reading tasks)$_{advanced}$	0.006	--	--	--
	(0.048)			
14. (Numeracy-ICT tasks)$_{advanced}$	--	0.067	--	--
		(0.075)		
15. (Reading-ICT tasks)$_{advanced}$	--	--	0.109	--
			(0.075)	
16. (Difference in tasks)$_{advanced}$	--	--	--	0.098
				(0.047)

Table 5a (cont.): The impact of task specialization on relative numeracy, literacy and problem solving (respondents with 10 or lower than 10 years of working experience)

Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
	(1)	(2)	(3)	(4)
17. (Numeracy-Reading tasks)$_{advanced}$*High school	0.015	--	--	--
	(0.051)			
18. (Numeracy-ICT tasks)$_{advanced}$*High school	--	0.012	--	--
		(0.078)		
19. (Reading-ICT tasks)$_{advanced}$*High school	--	--	0.009	--
			(0.075)	
20. (Difference in tasks)$_{advanced}$*High school	--	--	--	-0.001
				(0.048)
21. (Numeracy-Literacy tasks)$_{advanced}$*College	0.090*	--	--	--
	(0.049)			
22. (Numeracy-ICT tasks)$_{advanced}$*College	--	0.029	--	--
		(0.073)		
23. (Reading-ICT tasks)$_{advanced}$*College	--	--	0.029	--
			(0.073)	
24. (Difference in tasks)$_{advanced}$*College	--	--	--	0.047
				(0.045)
Average number of obs.	24,567	22,784	22,784	70,135
Average R squared	0.059	0.0485	0.0418	0.060

Source: PIAAC, sample of those with the three assessments (i.e., the sample excludes Italy, France and Spain)

Footnotes: a. The dependent variable is the individual-specific pairwise difference between the scores in the numeracy, literacy and problem solving assessments, each normalized by its s.d.

"Basic numeracy tasks" task is the fraction of all basic numeracy tasks that the respondents reports having performed in his or her job (current or last). The same definition applies to "Basic Reading" and "Basic ICT" tasks (See Table A1). The difference between two tasks measures the degree of specialization in one type of tasks. For example, "basic numeric - basic lit" takes value 1 if the individual performs all numeric tasks in his or her job and none of the literacy ones. The difference in sample sizes between column 1, on one hand, and 2 and 3, on the other, is that PSL is not available for exams done on paper.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of potential 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). We also include nine 1-digit occupation dummies, 22 industry dummies and country dummies. In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively. Standard errors account for heteroscedasticity and, in column 4, for arbitrary correlation within the observations of the same individual.

Table 5b: The impact of task specialization on relative numeracy, literacy and problem solving (respondents with more than 10 years of working experience)

	Sample of 15 countries conducting the three assessments			
Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
	(1)	(2)	(3)	(4)
1. (Numeracy-Reading tasks)$_{basic}$	0.059** (0.027)	--	--	--
2. (Numeracy-ICT tasks)$_{basic}$	--	0.142*** (0.034)	--	--
3. (Reading-ICT tasks)$_{basic}$	--	--	0.075** (0.038)	--
4. (Difference in tasks)$_{basic}$	--	--	--	0.049*** (0.018)
5. (Numeracy-Reading tasks)$_{basic}$*High school	-0.001 (0.029)	--	--	--
6. (Numeracy-ICT tasks)$_{basic}$*High school	--	-0.022 (0.042)	--	--
7. (Reading-ICT tasks)$_{basic}$*High school	--	--	-0.028 (0.036)	--
8. (Difference in tasks)$_{basic}$	--	--	--	-0.004 (0.022)
9. (Numeracy-Literacy tasks)$_{basic}$*College	-0.001 (0.032)	--	--	--
10. (Numeracy-ICT tasks)$_{basic}$*College	--	-0.087** (0.042)	--	--
11. (Reading-ICT tasks)$_{basic}$*College	--	--	-0.023 (0.041)	--
12. (Difference in tasks)$_{basic}$*College	--	--		-0.036* (0.021)
13. (Numeracy-Reading tasks)$_{advanced}$	0.023 (0.029)	--	--	--
14. (Numeracy-ICT tasks)$_{advanced}$	--	0.096** (0.042)	--	--
15. (Reading-ICT tasks)$_{advanced}$	--	--	0.056 (0.040)	--
16. (Difference in tasks)$_{advanced}$	--	--	--	0.088* (0.022)

Table 5b (cont.): The impact of task specialization on relative numeracy, literacy and problem solving (respondents with more than 10 years of working experience)

Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
	(1)	(2)	(3)	(4)
17. (Numeracy-Reading tasks)$_{advanced}$*High school	0.011	--	--	--
	(0.033)			
18. (Numeracy-ICT tasks)$_{advanced}$*High school	--	-0.026	--	--
		(0.042)		
19. (Reading-ICT tasks)$_{advanced}$*High school	--	--	0.041	
			(0.042)	
20. (Difference in tasks)$_{advanced}$*High school	--	--	--	0.004
				(0.023)
21. (Numeracy-Literacy tasks)$_{advanced}$*College	0.047*	--	--	--
	(0.029)			
22. (Numeracy-ICT tasks)$_{advanced}$*College	--	0.012	--	--
		(0.079)		
23. (Reading-ICT tasks)$_{advanced}$*College	--	--	0.070*	
			(0.041)	
24. (Difference in tasks)$_{advanced}$*College	--	--	--	0.071**
				(0.023)
Average number of obs.	45,425	36,714	36,714	120,000
Average R squared	0.059	0.0485	0.0418	0.059

Source: PIAAC, sample of those with the three assessments (i.e., the sample excludes Italy, France and Spain)

Footnotes: a. The dependent variable is the individual-specific pairwise difference between the scores in the numeracy, literacy and problem solving assessments, each normalized by its s.d.

"Basic numeracy tasks" task is the fraction of all basic numeracy tasks that the respondents reports having performed in his or her job (current or last). The same definition applies to "Basic Reading" and "Basic ICT" tasks (See Table A1). The difference between two tasks measures the degree of specialization in one type of tasks. For example, "basic numeric - basic lit" takes value 1 if the individual performs all numeric tasks in his or her job and none of the literacy ones. The difference in sample sizes between column 1, on one hand, and 2 and 3, on the other, is that PSL is not available for exams done on paper.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of potential 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). We also include nine 1-digit occupation dummies, 22 industry dummies and country dummies. In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively. Standard errors account for heteroscedasticity and, in column 4, for arbitrary correlation within the observations of the same individual.

Table 5c: The impact of task specialization on relative numeracy, literacy and problem solving (respondents 16-55)

	Sample of 15 countries conducting the three assessments			
Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
	(1)	(2)	(3)	(4)
1. (Numeracy-Reading tasks)$_{basic}$	0.071*** (0.025)	--	--	--
2. (Numeracy-ICT tasks)$_{basic}$	--	0.117*** (0.028)	--	--
3. (Reading-ICT tasks)$_{basic}$	--	--	0.083*** (0.031)	--
4. (Difference in tasks)$_{basic}$	--	--	--	0.089*** (0.016)
5. (Numeracy-Reading tasks)$_{basic}$*High school	-0.014 (0.028)	--	--	--
6. (Numeracy-ICT tasks)$_{basic}$*High school	--	-0.020 (0.032)	--	--
7. (Reading-ICT tasks)$_{basic}$*High school	--	--	-0.047 (0.030)	--
8. (Difference in tasks)$_{basic}$	--	--	--	-0.032 (0.019)
9. (Numeracy-Literacy tasks)$_{basic}$*College	-0.004 (0.029)	--	--	--
10. (Numeracy-ICT tasks)$_{basic}$*College	--	-0.073** (0.035)	--	--
11. (Reading-ICT tasks)$_{basic}$*College	--	--	-0.051 (0.033)	--
12. (Difference in tasks)$_{basic}$*College	--	--	--	-0.047* (0.019)
13. (Numeracy-Reading tasks)$_{advanced}$	0.018 (0.027)	--	--	--
14. (Numeracy-ICT tasks)$_{advanced}$	--	0.083** (0.040)	--	--
15. (Reading-ICT tasks)$_{advanced}$	--	--	0.070* (0.037)	--
16. (Difference in tasks)$_{advanced}$				0.077* (0.022)

Table 5c (cont.): The impact of task specialization on relative numeracy, literacy and problem solving (respondents 16-55)

Difference in normalized scores:	Numeracy -Literacy	Numeracy-Problem solving	Literacy-Problem solving	Difference in scores
17. (Numeracy-Reading tasks)$_{advanced}$*High school	0.012 (0.030)	--	--	--
18. (Numeracy-ICT tasks)$_{advanced}$*High school	--	-0.012 (0.041)	--	--
19. (Reading-ICT tasks)$_{advanced}$*High school	--	--	0.035 (0.036)	
20. (Difference in tasks)$_{advanced}$*High school	--	--	--	0.013 (0.023)
21. (Numeracy-Literacy tasks)$_{advanced}$*College	0.062 (0.027)	--	--	--
22. (Numeracy-ICT tasks)$_{advanced}$*College	--	0.023 (0.041)	--	--
23. (Reading-ICT tasks)$_{advanced}$*College	--	--	0.060 (0.035)	
24. (Difference in tasks)$_{advanced}$*College	--	--	--	0.066* (0.020)
Average number of obs.	69,992	59,498	59,498	80,996
Average R squared	0.059	0.0485	0.0418	0.059

Source: PIAAC, sample of those with the three assessments (i.e., the sample excludes Italy, France and Spain)

Footnotes: a. The dependent variable is the individual-specific pairwise difference between the scores in the numeracy, literacy and problem solving assessments, each normalized by its s.d.

"Basic numeracy tasks" task is the fraction of all basic numeracy tasks that the respondents reports having performed in his or her job (current or last). The same definition applies to "Basic Reading" and "Basic ICT" tasks (See Table A1). The difference between two tasks measures the degree of specialization in one type of tasks. For example, "basic numeric - basic lit" takes value 1 if the individual performs all numeric tasks in his or her job and none of the literacy ones. The difference in sample sizes between column 1, on one hand, and 2 and 3, on the other, is that PSL is not available for exams done on paper.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of potential 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). We also include nine 1-digit occupation dummies, 22 industry dummies and country dummies. In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

***,**,* over an estimate denote that the estimate is statistically different from zero at the 99th, 95th and 90th confidence level, respectively. Standard errors account for heteroscedasticity and, in column 4, for arbitrary correlation within the observations of the same individual.

Table 6: The impact of task specialization on relative numeracy, literacy and problem solving, by gender

	10 or less years of experience		Full sample	
	Males	**Females**	**Males**	**Females**
Difference in normalized scores:	Difference in scores	Difference in scores	Difference in scores	Difference in scores
$(\text{Difference in tasks})_{basic}$	0.072	0.147***	0.075***	0.090***
	(0.052)	(0.048)	(0.029)	(0.025)
$(\text{Difference in tasks})_{basic}$*High school	-0.022	-0.118**	0.012	-0.061**
	(0.057)	(0.054)	(0.032)	(0.028)
$(\text{Difference in tasks})_{basic}$*College	-0.035	-0.136***	-0.035	-0.064**
	(0.058)	(0.052)	(0.035)	(0.028)
$(\text{Difference in tasks})_{advanced}$	0.035	0.149*	0.064**	0.082**
	(0.050)	(0.077)	(0.027)	(0.038)
$(\text{Difference in tasks})_{advanced}$*High school	0.0043	-0.068	0.008	0.001
	(0.054)	(0.076)	(0.030)	(0.038)
$(\text{Difference in tasks})_{advanced}$*College	0.086	-0.013	0.067**	0.053
	(0.052)	(0.076)	(0.027)	(0.038)
Average number of obs.	32,344	39,177	89,223	99,765
Average R squared	0.060	0.060	0.059	0.059

Source: PIAAC

Notes: Sample of 15 countries exclude SP, IT and FR. Single-group sample is referred to a sample with individuals of the same education level. Estimations are only referred to basic, high-school or college individuals. Estimations are different by type of tasks and normalized scores

Table 7: The impact of tasks on numeracy and literacy scores by industries (All countries pooled)

	Sample with respondents between 16-55 years of age				
	Construction (F)	Manufacturing (C)	Retail (G)	Teaching (P)	Social services and health (Q)
	(1)	(2)	(3)	(4)	(5)
Dependent variable is the difference between normalized numeracy score and normalized literacy score					
1. (Difference in tasks)$_{basic}$	0.121*	0.091	0.097*	0.197	0.185***
	(0.072)	(0.059)	(0.052)	(0.137)	(0.067)
2. (Difference in tasks)$_{basic}$*High school	-0.032	-0.083	-0.005	-0.114	-0.070
	(0.078)	(0.068)	(0.061)	(0.150)	(0.070)
3. Impact on relative numeracy score of specialization among high school respondents = row 1 + row 2	*0.089*	*0.008*	*0.092*	*0.083*	*0.115*
4. (Difference in tasks)$_{basic}$*College	0.015	-0.100	-0.091	-0.110	-0.056
	(0.108)	(0.072)	(0.069)	(0.137)	(0.070)
5. Impact on relative numeracy score of specialization among college respondents = row 1 + row 4	*0.136*	*-0.009*	*0.006*	*0.087*	*0.070*
6. (Difference in tasks)$_{advanced}$	0.124**	0.041	0.120**	0.047	0.144**
	(0.055)	(0.051)	(0.049)	(0.114)	(0.061)
7. (Difference in tasks)$_{advanced}$*High school	-0.009	0.057	-0.051	0.059	-0.031
	(0.062)	(0.055)	(0.053)	(0.123)	(0.068)
6. (Difference in tasks)$_{advanced}$*College	-0.007	0.096	-0.056	0.188	0.009
	(0.074)	(0.063)	(0.056)	(0.117)	(0.063)
Average number of obs.	10,507	22,106	20,920	14,608	21,270
Average R2	0.069	0.075	0.056	0.045	0.053

Source: PIAAC

Note: The Table shows industry-specific effects of the impact on relative numeracy scores of specialization in basic numeracy tasks. The industries shown are ordered (from left to right) in decreasing intensity in numerical tasks. Averaging across all workers in the industry, construction is the most math-specialized industry (among the ones considered), followed by manufacturing, retail, teaching and social services (the least numeracy-specialized)

Table 8: The impact of cohort-level changes in reading tasks on cohort-level changes in literacy scores.

	Dependent variable: (Literacy score PIAAC 2012 - Literacy score IALS 1994)			
Basic school sample	(1)	(2)	(3)=(1)+country dummies	(4)=(2)+country dummies
1. (Fraction of time in basic reading tasks 2012) - (Fraction of time basic reading tasks 1994)	1.203**	1.120**	0.84**	0.72*
	(0.47)	(0.58)	(0.356)	(0.38)
2. (Fraction of time basic numeric tasks 2012) - (Fraction of time basic numeric tasks 1994)	--	-26.62	--	0.20
		(33.59)		(0.49)
Constant	-0.36	-0.38	0.36	0.36
	(0.08)	(0.14)	(0.08)	(0.08)
R-squared	0.12	0.149	0.88	0.889
High school sample				
3. (Fraction of time basic reading tasks 2012) - (Fraction of time basic reading tasks 1994)	0.614*	0.62*	0.04	0.02
	(0.361)	(0.361)	(0.44)	(0.46)
4. (Fraction of time in basic numeric tasks 2012) - (Fraction of time in basic numeric tasks 1994)	--	-0.04	--	-0.08
		(0.50)		(0.26)
Constant	-0.38	-0.48	-0.04	0.02
	(0.05)	(0.08)	(0.44)	(0.12)
College sample				
1. (Fraction of time in basic reading tasks 2012) - (Fraction of time basic reading tasks 1994)	2.42**	2.52**	-0.018	0.12
	(0.47)	(0.501)	(.37)	(0.507)
2. (Fraction of time basic numeric tasks 2012) - (Fraction of time basic numeric tasks 1994)	--	-28.8	--	0.149
		(0.42)		(0.506)
Constant	-0.54	-0.48	-0.092	-0.11
	(0.049)	(0.092)	(0.054)	(0.086)
Observations in each panel:	50 cells = (2 cohorts x 2 genders x 13 countries) minus 2 cells with less than 10 cases.			

Source: Pooled IALS(1994) and PIAAC (2012) samples, cohorts born between 1960 and 1969 and 1950 and 1959. The omitted country dummy is the US

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 TASKS						BASIC ICT TASKS			
			Elaborate budgets (Relative to the average)	Use calculator	Use fractions	Read diagrams	Read bills	Read emails (Relative to the average)	Read guides	Write emails	Read manuals	Write reports	Read articles	Using email (Relative to the average)	Using internet	Processing texts	Conducting transaction
11 Chief executives, senior officials and legislators	0.6	0	1.73	1.63	1.53	0.92	1.73	1.63	1.63	1.63	1.32	1.43	1.73	1.53	1.43	1.22	1.43
13 Production and specialised services managers	2.98	0	1.41	1.47	1.27	1.17	1.39	1.65	1.55	1.51	1.47	1.51	1.41	1.37	1.27	1.15	1.13
14 Hospitality, retail and other services managers	2.05	0.071	1.53	1.6	1.27	0.63	1.51	1.56	1.45	1.33	1.25	1.42	1.31	1.22	1.2	0.85	1.09
21 Science and engineering professionals	3.58	0	0.74	0.99	0.99	1.11	1.11	1.73	1.48	1.36	1.11	1.24	1.48	1.61	1.61	0.99	1.36
22 Health professionals	3.56	-0.276	1.44	0.87	0.87	0.87	1.44	1.73	1.44	1.73	1.73	1.73	1.44	1.73	1.73	1.73	1.44
23 Teaching professionals	6.63	-0.162	0.62	0.74	0.56	0.56	0.56	1.3	1.17	1.24	1.24	1.42	1.17	1.42	1.48	0.93	1.24
24 Business and administration professionals	3.76	-0.064	1.53	1.48	1.37	1.32	1.43	1.63	1.58	1.68	1.32	1.43	1.53	1.58	1.48	1.58	1.43
25 Information and communications technology professionals	2.12	-0.242	1.06	1.54	1.15	1.54	0.48	1.73	1.54	1.63	1.63	1.25	1.25	1.63	1.44	1.63	1.54
26 Legal, social and cultural professionals	3.22	-0.24	1.13	0.93	1,00	0.87	1,00	1.4	1.26	1.4	1.2	1.06	1.46	1.6	1.53	1.2	1.46
31 Science and engineering associate professionals	3.44	-0.14	0.54	1.31	0.93	1.14	0.59	1.26	1.54	1.17	1.43	1.27	0.93	1.32	1.29	0.78	0.93
32 Health associate professionals	2.59	-0.123	0.49	1.01	0.62	0.78	0.72	1.18	1.53	1.11	1.31	1.4	1.11	1.37	1.4	0.75	1.04
33 Business and administration associate professionals	6.34	-0.038	1.28	1.55	1.24	1.09	1.35	1.61	1.51	1.55	1.44	1.44	1.37	1.47	1.48	1.38	1.36
34 Legal, social, cultural and related associate professionals	2.59	-0.117	0.94	0.87	0.61	0.53	0.71	1.02	1.2	1.04	0.87	1.15	0.89	1.32	1.4	0.69	1.12
35 Information and communications technicians	0.8	-0.196	0.94	1.26	1.02	1.1	1.1	1.65	1.49	1.57	1.42	1.34	1.49	1.73	1.65	1.26	1.57
41 General and keyboard clerks	2.54	-0.079	0.8	1.29	0.75	0.7	1.03	1.58	1.35	1.44	0.91	1.34	0.94	1.38	1.32	1.35	1.15
42 Customer services clerks	2.86	-0.046	0.9	1.25	0.75	0.66	0.99	1.51	1.45	1.31	1.23	1.34	1.14	1.42	1.36	0.88	1.22
43 Numerical and material recording clerks	3.63	.003	0.74	1.21	0.86	0.66	0.87	1.22	1.27	1.14	1.04	1.23	0.89	1.35	1.31	0.93	1.1
44 Other clerical support workers	2.59	-0.108	0.74	1.18	0.74	0.74	0.85	1.45	1.44	1.27	1.05	1.42	0.96	1.27	1.27	1.01	1.12
51 Personal service workers	4.56	0.045	0.92	0.93	0.51	0.25	0.72	0.75	1,00	0.63	0.73	0.77	0.74	1.08	1.04	0.23	0.79
52 Sales workers	7.03	0.086	1.15	1.28	0.78	0.42	0.76	1.01	1.22	0.74	0.9	1,00	0.81	1.2	1.16	0.42	0.98
53 Personal care workers	7.05	-0.185	0.3	0.42	0.24	0.3	0.37	1.05	1.17	0.89	0.85	1.04	0.85	1.17	1.17	0.4	0.91
54 Protective services workers	1.65	-0.34	0.3	0.53	0.23	0.7	0.3	1.17	1.47	1.09	1.09	1.45	1.09	1.26	1.24	0.73	0.92
61 Market-oriented skilled agricultural workers	1.5	-0.008	1.01	0.93	0.65	0.55	1,00	0.87	1.14	0.72	1.01	0.86	0.87	0.66	0.66	0.27	0.52
71 Building and related trades workers, excluding electricians	3.88	0.047	0.74	1,00	0.83	0.91	0.67	0.72	1.2	0.57	1.08	0.85	0.56	1.01	0.97	0.21	0.74
72 Metal, machinery and related trades workers	2.71	0.021	0.5	1.01	0.71	1.04	0.46	0.76	1.36	0.6	1.17	1.02	0.64	1.04	1.03	0.23	0.84
73 Handicraft and printing workers	0.41	-0.045	0.52	1.25	0.8	0.69	0.42	0.9	1.32	0.83	1,00	1.04	0.66	1.14	1.07	0.42	0.9
74 Electrical and electronic trades workers	1.56	-0.112	0.48	1.12	0.8	1.3	0.64	1.12	1.65	0.91	1.52	1.14	0.8	1.41	1.46	0.51	1.09
75 Food processing, wood working, garment and other craft	1.22	0.0368	0.46	0.82	0.48	0.31	0.43	0.62	0.94	0.43	0.66	0.76	0.48	0.85	0.93	0.14	0.51
81 Stationary plant and machine operators	1.8	-0.061	0.21	0.84	0.4	0.59	0.18	0.7	1.26	0.53	0.9	0.93	0.48	1.01	1.05	0.17	0.78
82 Assemblers	0.52	0.008	0.14	0.81	0.33	0.66	0.26	0.57	1.16	0.5	0.76	0.85	0.45	1.04	1.09	0.28	0.78
83 Drivers and mobile plant operators	3.01	-0.039	0.53	0.79	0.4	0.88	0.63	0.86	1.28	0.59	0.95	1.14	0.68	1,00	1,00	0.17	0.83
91 Cleaners and helpers	2.67	-0.065	0.2	0.16	0.07	0.11	0.17	0.44	0.72	0.31	0.42	0.59	0.32	0.91	0.89	0.05	0.63
92 Agricultural, forestry and fishery labourers	0.59	0.004	0.36	0.29	0.22	0.14	0.31	0.14	0.48	0.14	0.36	0.21	0.26	0.54	0.57	0.02	0.31
93 Labourers in mining, construction, manufacturing and transport	2.31	-0.046	0.31	0.65	0.36	0.46	0.31	0.61	0.97	0.43	0.66	0.75	0.42	0.98	0.99	0.21	0.66
94 Food preparation assistants	0.67	-0.037	0.42	0.49	0.21	0.18	0.33	0.56	0.96	0.36	0.6	0.67	0.42	0.96	1,00	0.11	0.73
95 Street and related sales and service workers	0.05	0.348	1.57	1.1	0.94	0	0.63	0.16	0.31	0.31	0.16	0.31	0.63	0.47	0.63	0,00	0.16
96 Refuse workers and other elementary workers	0.93	-0.074	0.31	0.42	0.25	0.5	0.23	0.59	0.88	0.43	0.67	0.58	0.43	0.86	0.88	0.14	0.67
Mean			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Minimum			0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Maximum			1.73	1.63	1.53	1.54	1.73	1.73	1.65	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.57

Source: PIAAC

Footnotes: a. Sample of respondents with basic schooling 16 to 55 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 (0.40), write emails (0.38) and read guides (0.31). Main ICT tasks are use email (0.47), use internet (0.44), conducting transactions (0.42) and processing texts (0.41).