ANALYSING ADULTS' SKILLS: PROCEEDINGS OF THE 2ND INTERNATIONAL PIAAC CONFERENCE (HAARLEM, 2015)

OECD

BETTER POLICIES FOR BETTER LIVES

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FOREWORD

The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), offers a unique source of data regarding the skills of the adult population in 33 countries and economies across the globe.[1] At its centre is an assessment of literacy, numeracy and problem solving skills. This is combined with the collection of a wealth of background information that extends well beyond the usual socio-demographic characteristics collected in many surveys, to include measures of earnings, tasks performed on the workplace, practice of skills at home and at work, and non-economic outcomes like self-assessed health, trust in others, political efficacy, and participation in volunteering activities.

PIAAC continues an effort that started with the International Adult literacy Survey (IALS) in the mid- to late 1990s and the Adult Literacy and Life Skills Survey (ALL) in the early to mid-2000s. Its rationale lies primarily in the growing recognition of the contribution of human capital and skill development to individual life chances and well-being as well as to economy-wide outcomes such as productivity, economic growth, and the distribution of income. Skills are one of the main factors that allow individuals, and societies, to keep up with technological change, to adapt, to innovate; in one word, to prosper.

Against this background, it becomes crucial to gain knowledge about the current level of skills in the population and, more importantly, what can be done to help people in acquiring these skills, in maintaining them, and in putting them to the most effective use. To improve individuals' well-being, it is essential to help them to develop and use their talents to their full potential, to reduce the barriers associated with socio-economic background, unequal access to high quality education and other public services, discrimination and lack of meritocracy, and inefficiencies in the functioning of labour markets. A better understanding of the factors that facilitate or impede the development and maintenance of skills over the lifecycle as well as those that encourage the effective use of skills is vital for policy makers struggling with the question of how to respond to many of the trends that are transforming our economies and societies such as globalisation, digitisation and the ageing of the population.

What is true for the skills of individuals is just as true of the data from PIAAC: to benefit from them one must use them. As noted above, the PIAAC data represents an extremely rich source of information for the analysis of a wide range of issues, from both a policy and an academic perspective, related to education and the labour market.

Researchers around the world have not missed this opportunity. As of today, over 300 research papers and reports have been written using PIAAC data. There have been a number of conferences in the United States and Europe, in particular, that have specifically focussed on analysis using PIAAC data and a number of others are scheduled.

This volume collects a selection of papers from one such conference, jointly organised by the OECD and the Dutch Government in November 2015 in Haarlem, the Netherlands. A total of sixteen papers from

1. Data has been collected in two rounds the first took place in 2011-12 and involved 24 countries/economies and the second took place in 2014-15 in nine additional countries/economies.

the many high quality proposals that we received, were selected to be presented at the conference. One of the major objectives of the conference was to present analysis of the PIAAC data to an audience drawn largely from the policy community and to stimulate a fruitful dialogue between the policy and the research community.

The three papers collected in this volume represent the work of scholars who were invited to present their work in the plenary session of the conference. The authors are all renowned scholars in their respective fields. Each of the papers represents an important contribution to the better understanding of issues of labour market and education policy that are at the centre of the policy concerns of many governments.

In **Ageing and Literacy Skills: Evidence from IALS, ALL and PIAAC**, Garry Barrett and Craig Riddell investigate the link between skills and age: how skills proficiency evolves over the life-cycle, and how the skills proficiency of the population has changed over time across the different generations that have taken part in PIAAC and in previous surveys of adult skills. Their paper makes use of the fact that the assessment of literacy and numeracy in PIAAC was deliberately designed to be comparable with similar assessments undertaken in the two previous international assessments of these skills, IALS and ALL. The existence of several assessments taken at different points in time allows one to partly overcome one of the main limitations of cross-sectional data. Even if it is not possible to follow the same individuals over time in order to see how their proficiency evolves with ageing, the three surveys provide measures of the level of proficiency of representative samples of the same birth cohorts, assessed at different points in time. Combining data from the different surveys, the authors are able to separately estimate the effects of biological ageing (age effects) and birth cohort (cohort effects) on the observed age-proficiency profiles. Both effects are clearly extremely important.

The age effect tells us how skills increase and decrease over the lifespan of individuals. As improvements in medicine and in standards of living are bringing about higher life expectancies, and as fertility rates are declining, the population worldwide is getting older. In many countries, sustainability of pension systems has required the passing of reforms that have significantly increased the length of working lives. A better understanding of the evolution of skills over the lifecycle is therefore crucial to design policies that can support the proficiency (and therefore the productivity and the employability) of a large number of older adults.

The cohort effect provides information about the differences in the average proficiency of different generations, keeping age constant. This gives us an idea of how effective education and training systems have been over time in performing their tasks of endowing successive generations of young people with the set of skills they need to fully participate in societies and in the labour markets.

Unfortunately, in many countries there is evidence that younger generations are generally less proficient in literacy and numeracy than their older counterparts. As for the effect of biological ageing, a general tendency for proficiency to decline from around the age of 30 is observed in all countries. However, the large cross-country variation in the extent to which proficiency falls with increasing age suggests that policies can play an important role in minimising the negative effects of biological ageing.

Juan Francisco Jimeno, Aitor Lacuesta, Marta Martinez-Matute and Ernesto Villanueva investigate the extent to which work experience is a substitute for formal schooling in the acquisition of information-processing skills. This is a very relevant issue, especially in light of the interest in expanding access to work/study programmes that combine periods in the workplace with class-room based formal education. If such programs fail in equipping students with a broader set of general information-processing skills, they could damage employability in the longer run, when workers will perhaps be required to move to a different job or sector, in which the job-specific skills they acquired in the past are less valuable. In

Education, Labour Market Experience and Cognitive Skills: A First Approximation to the PIAAC Results, the authors provide evidence that schooling and work experience may be substitutes in terms of developing proficiency, although only for adults at the bottom of the schooling distribution. One of the interesting features of the paper is the authors' creative use of PIAAC. They use various econometric strategies to strengthen their findings, like exploiting the fact that PIAAC assesses proficiency in two domains (literacy and numeracy) to estimate individual fixed-effects model, thus reducing biases arising from individual unobserved heterogeneity. Essentially, by looking at relative proficiency in literacy versus numeracy, and relating them in the relative frequency with which workers perform literacy- or numeracy-related tasks in the workplace, they are able to account for any factor that is specific to a given individual, that is not observed by the researcher, and that could affect the outcome of interest (a concrete example in their setting could be general intelligence). The use of such econometric technique makes the authors much more confident in interpreting their finding as the causal effect of work experience (i.e. of performing certain tasks at work) on proficiency in information-processing skills.

Given the expansion of access to tertiary education that has occurred in most countries over recent decades, the possibility that the labour market is no longer able to absorb an increasing number of tertiary graduates is often raised by commentators and policy makers. In particular, there is a fear that university-educated individuals will face higher risks of being over-qualified for their job, with negative consequences in terms of wages, satisfaction, and well-being. Golo Henseke and Francis Green address this issue, in their **"Graduate Jobs" in OECD Countries: Analysis Using a New Indicator Based on High Skills Use**. Their contribution is both substantive and methodological. The authors propose a new indicator of "graduate jobs", which is based on the type of skills actually used on the workplace, rather than relying on the formal qualification the respondent possesses, or on a-priori classifications of occupations, or on self-reported (and therefore possibly biased) information about the match between qualification (or proficiency) and job requirements. When applied to PIAAC data, the new indicator reveals that almost 30% of jobs can be classified as graduate jobs and that, unlike with the traditional classifiers, several jobs in the occupation category "Technicians and Associate Professionals" can be considered as graduate jobs.

The papers collected in this volume confirm the high value of PIAAC data for academic and policy research, and the importance to investing in data dissemination activities to foster a dialogue between academia and policy circles. In line with its mission of encouraging the use of sound research to inform evidence-based policies, the OECD is organising, together with the Spanish government, a third international PIAAC conference, which will take place in Madrid in November 2016. In light of the work underway in preparation for the next cycle of PIAAC, planned for 2021, it is even more important to intensify the dialogue between the research and policy communities, because inputs from all relevant stakeholders are important in helping to design an even better and more useful instrument.

ACKNOWLEDGMENTS

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The volume was edited by Marco Paccagnella and William Thorn with production being co-ordinated by Jennifer Cannon. Marta Encinas-Martin was responsible for the organisation of the conference. The three papers included in this volume were written by (1) Garry Barrett and W. Craig Riddell, (2) Juan Francisco Jimeno, Aitor Lacuesta, Marta Martínez-Matute and Ernesto Villanueva and (3) Golo Henseke and Francis Green.

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AGEING AND LITERACY SKILLS: EVIDENCE FROM IALS, ALL AND PIAAC

Garry Barrett. Department of Economics, University of Sydney.

W. Craig Riddell. Vancouver School of Economics, University of British Columbia.

This paper examines the relationship between age and literacy using data from the International Adult Literacy Survey (IALS), the Adult Literacy and Life Skills Survey (ALL) and The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). A negative partial relationship between literacy and age exists with literacy declining with age, especially after age 45. However, this relationship could reflect some combination of age and birth cohort effects. The analysis shows that in most participating countries the negative literacy-age profile observed in cross-sectional data arises from offsetting ageing and cohort effects. With some exceptions, more recent birth cohorts have lower levels of literacy and individuals from a given birth cohort lose literacy skills after they leave school at a rate greater than indicated by cross-sectional estimates. The results for birth cohort suggest that there is not a general tendency for literacy skills to decline from one generation to the next, but that the majority of the countries examined are doing a poorer job of developing literacy skills in successive generations.

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1. Introduction

In this paper,[1] we study the relationship between age and literacy skills using data from the International Adult Literacy Survey (IALS) carried out in the 1990s, the International Adult Literacy and Life Skills Survey (ALL) carried out in the 2000s and the recent Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). When it is possible to do so we use data from countries that participated in all three surveys: Australia, Canada, Italy, the Netherlands, Norway and the United States. We also carry out a similar analysis for the countries that participated only in the IALS and PIAAC rounds of international comparative data collection on adult skills: Denmark, Finland, Ireland, Sweden and Flanders (Belgium).[2]

The IALS, ALL and PIAAC surveys are unique in providing measures of literacy and numeracy skills for a representative sample of the adult population. These surveys combine methods of educational testing with household survey techniques, and also provide detailed individual and demographic information on respondents. A key objective is to assess skills used in daily activities – at work, in the home, and in the community. In other words, these are basic cognitive skills used in daily life. Our focus is on literacy skills as these were assessed in all three surveys. In IALS and ALL separate measures of prose literacy and document literacy were provided, while in PIAAC these are combined into a single literacy measure.

Previous research using the Canadian IALS and ALL data found that there is a weak negative relationship between literacy skills and age, after controlling for other influences (Green and Riddell, 2003, 2013; Ferrer, Green and Riddell, 2006). Green and Riddell (2013) also found a similarly weak relationship between these variables in Norway and the United States. In this paper we begin by investigating the relationship between literacy skills and age in the countries that participated in IALS, ALL and PIAAC, as well as IALS and PIAAC. Again, we find that in all countries examined the partial relationship between literacy skills and age is negative in direction (i.e. literacy skills decline with age, holding constant other influences on literacy). The steepness of the literacy-age gradient does, however, vary considerably across countries. The absence of a positive relationship over at least some age range between basic cognitive skills such as literacy and age is perhaps surprising as individual earnings typically increase with age, albeit at a decreasing rate. The common finding of positively sloped age-earnings profiles is generally attributed to accumulation of human capital with work experience over the life cycle.[3] Taken at face value, these results suggest that the relationship between literacy skills and age does not follow the pattern displayed by other forms of human capital.

However, the relationship between skills and age in cross-sectional data could reflect some combination of age and cohort effects. A 35-year-old in 2012 may differ from a 25-year-old in 2012 both because she is older and because she comes from an earlier birth cohort. Those born in different time periods may experience differences in the nature and quality of schooling and work experience, as well as differences in the contributions of other influences on skills such as parents and peers. In order to distinguish between age and cohort effects, we use the IALS, ALL and PIAAC data to create synthetic cohorts. Each of these surveys provides information on a representative sample of the adult population at a

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1. An earlier version of this paper was presented at the OECD 2nd International PIAAC Conference in Haarlem, the Netherlands in November 2015. We thank our discussant John Martin and conference participants for their helpful comments.

2. Four additional countries participated in IALS and PIAAC: the Czech Republic, England/Northern Ireland, Germany and Poland. However, in these countries educational attainment, a crucial variable in our analysis, is unreliable. Thus, we do not examine these countries.

3. Other explanations include internal labour markets and incentive-based pay structures in which wages rise more rapidly with seniority than does worker productivity.

point in time. Thus, 26-35 year-olds surveyed in 1994, 35-44 year-olds surveyed in 2003 and 44-53 year-olds surveyed in 2012 are all representative samples of the 1959-68 birth cohort. Our analysis focuses on literacy, which is measured in a comparable way in the three surveys.[4] For the countries that participated in IALS, ALL and PIAAC we study birth cohorts that appeared in each of the three surveys. For example, for Canada the three surveys were nine years apart so with appropriate age data[5] it is possible to observe representative samples of the following birth cohorts in all three surveys:[6]

1959-1968 birth cohort:

- Age in IALS 1994: 26-35
- Age in ALL 2003: 35-44
- Age in PIAAC 2012: 44-53

1949-58 birth cohort:

- Age in IALS 1994: 36-45
- Age in ALL 2003: 45-54
- Age in PIAAC 2012: 54-63

In addition, we can examine representative samples of the following birth cohorts in two of the three surveys:

1969-1978 birth cohort:

- Age in ALL 2003: 25-34
- Age in PIAAC 2012: 34-43

1939-1948 birth cohort:

- Age in IALS 1994: 46-55
- Age in ALL 2003: 55-64

In the case of countries that did not participate in ALL we study birth cohorts that appeared in both IALS and PIAAC.

Before the cohort analysis we examine the factors that influence literacy skills using the PIAAC data. This investigation yields several noteworthy results. In all of the countries, literacy increases strongly (though at a decreasing rate) with years of schooling. Parental education levels also have a positive association with literacy, but what matters most is having a mother or father with at least a high school education. Parental immigrant status plays no role in Canada and the United States but does influence literacy (principally in a negative manner) in Australia and the European countries. Perhaps most important for this study, we find a negative relation between age and literacy in each country. There is no evidence

4. The IALS and ALL data on prose and document literacy have been re-scaled to be comparable to the PIAAC measure of literacy, which combines both prose and document literacy. In our analysis we use the re-scaled data.

5. Specifically, because the surveys are not exactly 10 years apart, our synthetic cohort analysis requires age measured in years rather than 5-year or 10-year categories. Continuous age data allow us to select specific age groups in each survey such that they provide representative samples of the same birth cohort.

6. We can also study younger and older cohorts that participated in two of the three surveys.

that literacy increases with age beyond that attained by the youngest cohort (25 to 34 year-olds).[7] This relationship is approximately flat until the mid-40s, and then literacy declines at a rate that is initially modest in size but becomes larger for the older age groups. At first glance, these results appear to imply that individuals acquire their literacy through formal schooling and through the efforts of their parents but that their literacy levels do not develop further (and, indeed, subsequently decline) upon leaving school. However, these cross-sectional estimates combine age and cohort effects.

We then extend previous research of Green and Riddell (2013) who use the IALS and ALL data for Canada, Norway and the United States. They show that in these countries the relatively modest negative slope of the profile of literacy relative to age in the cross-sectional IALS and ALL datasets actually arises from a combination of offsetting ageing and cohort effects. In particular, Green and Riddell (2013) find that individuals from a given birth cohort lose literacy skills in the years after they leave school at a rate that is typically greater than is indicated by cross-sectional estimates. At the same time, their evidence indicates that more recent birth cohorts have lower levels of literacy. Thus, 35-year-olds in ALL 2003 have approximately the same average literacy score as 25-year-olds in the same survey not because 25-year-olds should expect to be at the same literacy level in 10 years but because the 35-year-olds started from a higher literacy level at age 25 (i.e. come from a more literate cohort) but lost some of their initial literacy skills during the time since they left school. Their results suggest, at least in the case of Canada, Norway and the United States, a tendency for literacy skills to decline over time at a rate greater than is suggested by cross-sectional data. This paper extends the previous analysis of Canada, Norway and the United States to incorporate the recently available PIAAC data, as well as to examine a broader range of countries. We present results for the six countries that participated in IALS, ALL and PIAAC (Australia, Canada, Italy, the Netherlands, Norway and the United States) and five countries that participated in IALS and PIAAC (Belgium, Denmark, Finland, Ireland and Sweden). In addition to data availability, these countries are of interest for several reasons, including the fact that they provide a wide range of literacy levels and the extent of inequality in their literacy distributions.

The paper is organised as follows. The next section describes our data and reports summary statistics. Section three analyses the generation of literacy skills using the cross-sectional PIAAC data for the six countries that participated in the three surveys. In the fourth section we employ “synthetic cohorts” analysis to estimate separate age and cohort effects using the IALS, ALL and PIAAC data. The final section concludes.

2. Data

Our data comes from The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), a fascinating survey carried out in over 20 OECD countries and economies in 2011-2012. We also make use of the International Adult Literacy Survey (IALS) and International Adult Literacy and Skills Survey (ALL), earlier surveys of literacy skills carried out in the 1990s and 2000s respectively. These surveys represent a breakthrough in providing detailed assessments of the cognitive skills of representative samples of the adult population, assessments that are comparable across countries and language groups. They include standard questions on demographics, labour force status and earnings, but also measure literacy, numeracy and related cognitive skills. A key objective of these assessments is to go beyond testing proficiency in mathematics and reading in order to assess capabilities in applying these cognitive skills to situations found in everyday life.

Our goal is to focus on literacy generation in each country’s society and economy and, as a result, we exclude from our samples those born in another country, whose skills were not influenced by the country’s

7. In a few countries the literacy proficiency of the 35-44 year age group is a bit greater than that of the youngest age category but the differences are never statistically significant at the 5% level.

educational system. Where appropriate, we also drop observations on aboriginals, whose schooling system and skills are generally very distinct from those of others born in the country of interest. The surveys cover individuals over age 15 but we restrict the analysis to those ages 25 and over in order to focus on those who have completed formal schooling. This sample restriction is necessary when using the synthetic cohort methodology in order to ensure that the age cohorts used in the analysis are representative of the overall population in that cohort. Our analysis focuses on those who have completed formal schooling, and thus have received the contribution made by the formal education system to their literacy skills. In the case of the youngest age group (those ages 15–24), many are still in school. Furthermore, the fraction of the youngest cohort that remains in school is changing over time due to rising educational attainment in most countries. Thus it is not meaningful to compare those in the youngest cohort who have finished formal schooling from one generation to another – doing so would violate the conditions under which the synthetic cohorts methodology is valid.

In the case of Canada, which has the largest sample size for IALS, ALL and PIAAC, the result is analysis samples of 2 982 for IALS, 13 464 for ALL and 17 898 for PIAAC. These samples are used in our analysis of the relationship between age and literacy skills in Canada. PIAAC analysis sample sizes are much smaller for the other countries – generally between 3 000 and 4 000 observations. We include both males and females but control for gender throughout. Finally, we use the sample weights provided with the data in all tables and estimation; thus in each country all summary statistics and regression estimates are representative of the adult native-born non-aboriginal population age 25 and above.

Table A.1 (see Annex A) reports summary statistics for our samples drawn from the Canadian PIAAC, ALL and IALS data. The literacy test outcomes are scaled to fall between 0 and 500, with average literacy scores equal to 268 in IALS, 274 in ALL and 271 in PIAAC. Females are slightly over-represented in the sample relative to the population but we control for gender in all of our estimates. The average number of years of completed schooling (13.7 in PIAAC) is typical of what is found in other Canadian surveys. Also noteworthy is the substantial increase in years of completed schooling between 1994 and 2012. Comparing educational attainment of respondents to that of their parents indicates strong progress in education across generations. This progress is also evident in the substantial decline in the fraction of parents who are high school dropouts between 1994 (IALS) and 2012 (PIAAC). The fact that only 7% to 8% of respondents have an immigrant mother or father in a country in which immigrants represent about 20% of the population can be attributed to our sample being restricted to native-born Canadians. The birth cohorts are ordered from youngest to oldest. As can be seen in Table A.1, 2 of the six birth cohorts appear in all three surveys and an additional two appear in two of the three surveys. The youngest and oldest birth cohorts are represented in only one of the three surveys.

3. The generation of literacy skills

In this section we use PIAAC data to examine the determinants of literacy in cross-sectional data. We begin with Canada, the country with the largest sample size, and then examine the other countries that participated in IALS, ALL and PIAAC: Australia, Italy, the Netherlands, Norway and the United States. Our dependent variable is the log of the literacy score so our estimated coefficients can be interpreted as showing impacts of each explanatory variable in terms of percentage changes in literacy.

Before presenting the estimation results, we begin by setting out a brief, heuristic model of literacy generation. The model will help to put our estimates in context as well as providing guidance in thinking about statistical issues. Consider a simple model in which individuals start out at birth endowed with two key characteristics: their ability and parental resources. By parental resources, we mean something quite broad, incorporating both parental income and parental willingness and ability to support their children's education and literacy acquisition. Pre-school children begin to acquire literacy based on these fundamental characteristics. Once they enter school, ability and parental resources interact with characteristics of the school such as teacher quality, class size and the attitudes and abilities of peers. New additions to literacy with each year of schooling are then functions of individual ability, parental resources, school characteristics and the literacy level at the beginning of the period. These influences may interact in complicated ways. These additions continue until the legal school leaving age. After that point until the end of high school, students make a decision each year on whether to continue in school. That decision will be a function of ability, parental resources and school characteristics, but it is also likely to be a function of literacy acquired to that point. The more literate a student is, the less onerous they are likely to find school and the more likely they are to choose to stay an extra year. Finally, after high school, whether an individual continues to go to school will be determined by a combination of their own decision to apply to continue and the decision of the college or university on whether to admit them. The latter decision will likely be a function of the student's literacy as reflected in her grades. Thus, schooling and literacy are co-determined with extra years of schooling leading to increased literacy but increased literacy also leading to more years of schooling, especially after the legal school leaving age. Indeed, once we account for expectations, the inter-relation between the two may be even tighter. Individuals who do not expect to continue with school past the legal minimum may rationally under-invest in acquiring literacy skills while they are in school.

Once individuals leave school, literacy acquisition is likely more difficult. Literacy skills may be acquired on the job if they are needed for carrying out tasks at work but otherwise further acquisition would require active investment in non-work hours. Indeed, it seems quite possible that individuals could lose literacy skills after they leave formal schooling if those skills depreciate when they are not used.

We are interested in characterising the components of literacy generation, especially in whether literacy declines or rises after leaving school and how this ageing process is related to individual characteristics. If literacy has a "use it or lose it" form then there may be a case for adopting policies that encourage literacy maintenance and "lifelong learning" activities. Also of interest is the relationship of literacy to parental characteristics and resources as well as the linkage between formal schooling and literacy since this is a main channel through which one could hope to influence literacy outcomes. Many of the parameters of interest reflect causal relationships that are difficult to establish definitively because of unobserved factors that may be correlated with both literacy and education. We are fortunate in having data that allow us to control for family background, a key influence that is not observed in many data sources. Nonetheless, there may be other variables that we do not observe and that are correlated with literacy and education or age. Thus our findings are best interpreted as partial correlations that control for a rich set of observables rather than as causal impacts.

The first column of Table A.2a (see Annex A) presents our simplest OLS regression in which the dependent variable is the log of the individual literacy score in Canada and the independent variables are age in 10-year categories, years of schooling, years of schooling squared, and a gender dummy. The coefficient on the gender dummy indicates that there is a statistically significant difference in literacy between men and women conditional on age and education but that this gender gap is small in size (less than 1%).[8] The other variables are also statistically significantly different from zero at the 1% level. The age coefficients imply that the impact of an extra decade of age on literacy (relative to the omitted category, those aged 25-34) is a modest 1.3% decline over one decade but increasingly large declines of 4.2% and 5.7% after 20 and 30 years respectively. The relationship that is economically most substantial is that between literacy and formal schooling. One extra year of schooling, evaluated when the individual

8. In previous analysis with IALS and ALL data we found that females achieve higher scores on prose literacy than do males, and the reverse is true for document literacy. These offsetting coefficients in the individual score regressions resulted in a small and insignificant coefficient in the regression for the average score. The gender coefficient in PIAAC is larger in size and statistically significant, but is nonetheless quantitatively small.

already has 12 years of education, increases literacy by 3.6%. The non-linear (concave) nature of this relationship implies that there are diminishing returns to additional years of schooling. This feature probably reflects the fact that PIAAC assesses basic cognitive skills rather than higher order skills.[9]

As discussed earlier, literacy and years of schooling are likely to be jointly determined. In that case, OLS estimates are likely to suffer from omitted variables bias. Although most attention focuses on the estimated impact of schooling on literacy, other coefficients (including those on age) could also be biased. Such biases may arise because of a correlation between literacy and schooling arising from unobserved variables that are correlated with both education and literacy. One important set of variables that is often not available consists of parental and family background characteristics. Fortunately with the PIAAC data we are able to control for a variety of family background factors including educational attainment and the immigrant status of the respondent's mother and father.

In the second column of Table A.2a we add variables on parental education and parental immigrant status, allowing mothers and fathers to have separate influences. Introducing these variables has only a small impact on the gender coefficient, but it does have the expected consequence of reducing the coefficient on years of schooling, consistent with the view that parental education exerts an influence on both the child's educational attainment and her literacy skills. The estimated impact of an additional year of school evaluated at 12 years of schooling falls from 3.6% to 3.2%, a decline of about 10%. Interestingly, including parental background leads to a noteworthy decrease in the absolute value of age coefficients. Relative to the omitted age group (those 25-34 years of age), there is now no significant change in the next 10 years and smaller declines in literacy of 2.5% and 3.3% after 20 and 30 years respectively. This result suggests that it is important to control for family background when examining the relationship between literacy skills and age. Omitting family background may result in over-stating the extent to which literacy declines with age in cross-sectional data.

The parental education variables are jointly highly significantly different from zero but, perhaps surprising, the effect is found mainly at low levels of parental education, a result also found in Green and Riddell (2013) with Canadian ALL data. Having a mother who is a high school dropout decreases average literacy by more than 3%, and having a father with less than high school education is associated with literacy levels about 1% lower. However, parental education beyond high school graduation has no (in the case of mothers) or relatively modest (in the case of fathers) further impacts on literacy. Interestingly, not knowing (or reporting) a parent's education level – which is the case for 5 to 7% of our sample -- has a strong effect, being associated with approximately 6% lower literacy. While we included this variable in order to allow us keep the observations with missing information on parental education, it seems possible it represents something real. For example, children who do not know a parent's education likely did not have a close relationship with that parent. Thus, the estimated coefficient may reflect the extent to which literacy is generated through direct parental involvement. Finally, having a mother or father who is an immigrant has no association with literacy, after controlling for other influences. Overall, the results point to a surprisingly weak association between literacy and parental background, although controlling for family background is important for obtaining estimates of the impact of schooling and age that are less affected by omitted variables bias. Formal schooling has the most substantial impact on literacy generation.

The third column replaces the specification based on 10-year age categories with a less restrictive specification using 5-year age categories. The omitted age category remains the same as in column 2 – those aged 25-34. The 5-year age category specification yields a slightly better fit. The implications of the estimates are very similar. Relative to the omitted category, literacy declines gradually with age – for

9. Previous research with IALS and ALL data also found diminishing returns to additional education (e.g. Green and Riddell, 2003, 2013).

example by 2% to 3% for those 45-49 and 50-54 years of age respectively and 3% to 4% for the two oldest age groups.

Columns 4 to 6 report estimates for the same specifications as columns 1 to 3 except that respondent's education is measured in levels rather than in years of completed schooling. High school graduates without post-secondary education are the omitted category. The overall fit is not as good as was obtained with the quadratic years of schooling specification. Importantly, however, the estimated coefficients associated with gender, age of respondent and family background are virtually unchanged. These estimates indicate that high school dropouts have literacy skills 15% to 17% lower than high school graduates, and university graduates have literacy levels 12% to 14% higher. There is also a small 3% to 4% improvement in literacy for those with some post-secondary education below the university level.

Three key findings follow from the estimates reported in Table A.2a. First, the estimates indicate that education has a strong effect on literacy and that formal schooling is the dominant determinant of literacy. This result is robust to controlling for family background, although the partial effect of education on literacy skills is over-stated (albeit modestly) when family background is not included as a control. Parent's education also plays a role, but its influence is quantitatively modest and mainly restricted to parents with low levels of formal education. The second conclusion is that, in cross-sectional Canadian data, literacy gradually declines with age, beginning in the mid-40s, but at a modest rate. The third finding is that the relationship between literacy with age is correlated with family background. As a consequence, the decline of literacy skills with age is over-stated when parents' education and immigrant status is not included as a covariate in skill production equations.

Tables A.2b to A.2f report similar estimated log skill regressions using PIAAC data for the United States, Norway, the Netherlands, Italy and Australia. Several generalisations emerge from these estimates. First, the pattern of skill decline with age in cross-sectional data is evident in each of these countries. In general there is not a statistically significant difference in literacy skills between the omitted 25-34 year-old group and those aged 35-44. However, lower skills are evident among the older age groups, with the largest decline being that for the oldest age groups. The rate at which literacy falls with age is smaller than that in Canada in some countries (such as Italy and the United States), similar in Australia, and much larger in others (such as the Netherlands and Norway). A second noteworthy finding common to these countries is that controlling for family background results in a reduction in the rate at which literacy skills are estimated to decline with age. The extent to which controlling for family background alters the estimated partial correlation between literacy skills and age differs across countries, being least important in the Netherlands and most important in Canada and the United States. Many studies have found that parents' education and other dimensions of family background exert an important influence on educational attainment and skill accumulation. This result suggests that family background may also influence the rate at which skills depreciate over the life cycle.

Another result common to these countries is that respondents with a mother and/or father with low educational attainment (less than high school completion) have lower literacy levels, after controlling for other factors. Interestingly, however, having parents with post-secondary education has either no impact on literacy or a positive effect that is modest in size. This suggests that the main way that highly educated parents influence the literacy skills of their children is indirectly, by influencing their educational attainment, rather than directly.

Immigrant status of parents matters in Australia and the European countries, most prominently in the Netherlands, but does not affect literacy skills of respondents in North America. In Norway and the Netherlands those with immigrant parents have somewhat lower literacy, other things equal. In Italy having an immigrant mother is associated with higher literacy, while the opposite is the case for those with an immigrant father. Australia is the opposite to Italy: having an immigrant mother is associated with lower literacy, but literacy levels are slightly higher for those with immigrant fathers, after controlling for other influences. In all countries, the influence of parental immigrant status may operate through language as the literacy tests are carried out in the official language (or languages) of the country in which the respondent lives.

Formal schooling exerts a strong influence on literacy in each country. The strength of the partial correlation is greatest in Canada and the United States but in all these countries education is the major influence on literacy skills.

4. Age and cohort effects

One of the most striking results from the Table 2 regressions is that literacy skills decline (albeit at a slow rate) with age, beginning in the mid-40s. Prior to the mid-40s there is no increase in literacy; indeed, the coefficient estimates suggest a slight decline albeit one that is not statistically significant. Taken at face value, this suggests that, on average in a wide range of countries, individuals do not enhance their literacy skills after they finish schooling. Essentially, literacy is acquired principally at school with some contribution from their parents, and then declines, albeit gradually at first.

However, interpreting the coefficient on age in a cross-sectional regression requires some care. Differentials between two age groups in a cross section could reflect a variety of possible combinations of true age and cohort (or generational) effects. Thus, while we are tempted to view the literacy level of 35-year-olds in the PIAAC as a reflection of the literacy level the 25-year-olds are likely to be at in 10 years' time, we need to bear in mind that the 35-year-olds come from an older generation and their observed literacy reflects a combination of any generational differential as well as an ageing effect. Only if there are no systematic differences across birth cohorts does the cross-sectional literacy-age profile reflect the true impact of ageing on literacy.

A more complete investigation of cohort and ageing effects requires the use either of true panel data or of at least two cross-sectional datasets constructed in such a way that we can follow "synthetic" cohorts through time. Synthetic cohorts take advantage of the fact that although we do not necessarily observe the same people at different points in time, we do observe representative samples of the population at different points in time. From these samples we can construct representative samples of individuals from the same birth cohort, thus creating a quasi-panel data set from a common birth cohort. We will make use of the IALS, ALL and the PIAAC for this purpose. For example, in the public use version of the IALS (which was carried out in 1994 in Canada), we can observe a set of 10-year age groups for the respondents (i.e. ages 16-25, 26-35, 36-45, 46-55, 56-65). We can also construct age groups in ALL and PIAAC that correspond to the age people in these birth cohorts would be 9 years later in ALL (i.e. 25-34, 35-44, 45-54, 55-64, and 65-74) and 18 years later in PIAAC.[10] Since the three surveys provide representative samples of the adult population, it follows that each provides an unbiased estimate of the literacy distribution for these birth cohorts at three different points in time and we can follow the progress of a given cohort over time. Throughout the analysis we use versions of IALS and ALL that have the re-scaled literacy scores (essential for comparability over time).

To illustrate the age and cohort effects we plot the densities of the literacy distribution from the Canadian samples. Figure A.1 shows the overall distribution of literacy in ALL 2003 and PIAAC 2012. This figure indicates that there has been a noticeable deterioration of literacy in Canada over this 9-year

10. The Canadian public use IALS and ALL data are limited to 10-year age categories. However, the age groups in IALS and ALL data differ by one year, being 16-25, 26-35, etc. in IALS and 15-24, 25-34, etc. in ALL. Because IALS and ALL are nine years apart, we are able to align the age groups in IALS, ALL and PIAAC to provide representative samples of each birth cohort.

period. Throughout most of the range of literacy scores the 2012 distribution lies to the left of the corresponding 2003 distribution. The large sample sizes of the Canadian ALL and PIAAC surveys enables us to show breakdowns by age and birth cohorts. Thus, in Figure A.2, we present the density plots for individuals who are age 25 to 34 in 2003 and individuals who are the same age in 2012. These densities correspond to the literacy for the youngest cohort we examine in 2012 and for the cohort just before them at the same age (observed in 2003). The density for the younger cohort (observed in 2012) has more spread, with both the left and right tails being thicker, especially that of the lower tail. In other words, the younger cohort experiences deterioration in literacy at the low end of the distribution but a slight improvement at the top end. This pattern is reflected in a 10th percentile of 250 and a 90th percentile of 341 in 2003 compared to values of 236 and 342, respectively, in 2012. The reduction in the lower tail is much larger, as reflected in a median value of 294 in 2003 compared to 303 in 2012. Except for the small improvement at the very top of the distribution, literacy proficiency of this age group fell substantially.

In Figure A.3, we present the same density comparison for individuals aged 35 to 44. The outcome is similar to Figure A.2 except that the relative worsening in the lower end of the distribution is not as great and neither is the relative improvement at the very top. For example, the median score fell from 296 in 2003 to 292 in 2012. In contrast, Figure A.4 shows that for the 45 to 54-year-olds, the results in 2012 are worse across the distribution. Finally, Figure 1.A1.5 also shows that those aged 55 to 64 made improvements over time at the bottom of the literacy distribution, but experienced inferior outcomes at the very top end. The 10th percentile rose from 198 in 2003 to 217 in 2012, but the 90th percentile score dropped slightly (from 323 to 321).

The fact that we see different patterns across age groups is important, in part, because observing different relative changes between 2003 and 2012 for different groups suggests that we are witnessing something real rather than just a difference in the tests in the two years. If all plots for all groups showed deterioration at the bottom and slight improvement at the top between ALL and PIAAC, then the simplest explanation for the patterns would be that the test changed in such a way that it generated lower scores on the easier questions that will constitute most of the values at the bottom but better results on the harder tests that will define the shape of the top of the distribution.

We now turn to the analysis of the effects of ageing on literacy skills. Figures A.6 to A.8 present density plots for each year for specific birth cohorts. Note that this contrasts with Figures A.2 to A.5 that examine people of the same age in the two surveys. Figures A.2 to A.5 make comparisons across groups at the same age at different points in time while the Figure 1.1A.6 to 1.A1.8 comparisons follow individual birth cohorts through time. Figure A.6 shows the plots for the 1969-1978 birth cohort: this cohort was age 16 to 25 in 1994, age 25 to 34 in 2003 and 34 to 43 in 2003.[11] The plot indicates deterioration of literacy proficiency between 2003 and 2012 throughout the distribution and an increase in the spread of the distribution. The 10th percentile of the literacy distribution decreases by 20 points (from 250 to 230) for this cohort while the median falls by 10 points from 303 to 293. The decline at the very top is relatively modest – the 90th percentile falls from 341 to 339.

The 1959-196 birth cohort (individuals who were age 26 to 35 in 1994, age 35 to 44 in 2003 and age 44 to 53 in 2012) is plotted in Figure A.7. Between the first two surveys (IALS 1994 and ALL 2003) there is little change at the bottom of the skill distribution but a clear worsening at the top. In contrast, the shift in the skill distribution between 2003 and 2012 shows a very similar pattern to that in Figure A.6 and even greater decline in literacy. The median falls 17 percentage points from 296 to 279 and the 10th percentile declines by 21 percentage points (from 233 to 212). The decline in the 90th percentile is more modest (7 percentage points) but nonetheless substantial.

11. The 1994 distribution is not shown because it would not be representative of the 1969 to 1978 birth cohort, as discussed previously.

Finally, the densities for the 1949 to 1958 birth cohort (those age 36 to 45 in 1994) show similar patterns between each pair of surveys but the magnitudes of the shifts are even larger (Figure A.8). Between 1994 and 2003 there is a substantial decline in literacy at the top of the distribution but little change at the bottom (scores below 235). Between 2003 and 2012 a dramatic deterioration is evident, especially in the top half of the distribution. For example, the median falls 20 percentage points from 288 to 268 and the 90th percentile decreases 16 percentage points from 335 to 319 between the survey years.

Overall, across these three birth cohorts covering those born in the decades of the 1950s, 1960s and 1970s, the pattern of the shifts in the skill distributions between IALS and ALL and those between ALL and PIAAC are broadly similar across birth cohorts but differ between the two time periods. Between 1994 and 2003 there is a decline in literacy at the top of the distribution but little change in the bottom. Between 2003 and 2012 a substantial decline in literacy is evident throughout most of the distribution, especially in the lower half. The magnitudes of the changes between IALS and ALL and between ALL and PIAAC appear to become more pronounced with age.

The fact that the patterns for the three birth cohorts are broadly similar (but differ in magnitudes) does raise questions about the comparability of the data between the three surveys. However, the differences in patterns across age groups discussed previously works against this explanation. A more likely explanation of the patterns is that literacy skills deteriorate after leaving school but that the rate of deterioration increases with age.

To quantify the age and cohort effects, we pool the IALS, ALL and PIAAC data[12] and add cohort dummies to the cross-sectional specifications used in Table A.2.[13] We report the results from this cohort specification for Canada in Table A.3a. Columns 1 and 3 show estimates for the pooled sample that correspond to those reported in Table A.2 for the PIAAC sample. These estimates are very similar to those shown in Table A.2. Columns 2 and 4 include the cohort dummies, allowing us to separate age and cohort effects. As in the earlier specification, the schooling variables enter strongly and significantly. With or without the cohort controls, the schooling effect is very similar to that we witnessed in Table A.2 based on cross-section data. The parental education variables exhibit the same patterns as in earlier estimation, with low as well as unknown/not reported parental education having a large negative impact but the remaining variables having small and insignificant coefficients. Parental immigrant status has little (in the case of mothers) or no (in the case of fathers) impact on the respondent's literacy skills.

The age and cohort effects in the pooled Canadian ALL and PIAAC sample show interesting patterns that mirror earlier findings of Green and Riddell (2013) using IALS and ALL data. Recall from Table A.2 that when we estimate our standard specification with dummies for age categories, we find a cross-sectional age profile with a small negative slope for much of the age range. This cross-sectional finding is replicated in Table A.3a using the pooled sample. In particular, in column 3 (which controls for family background), the first age dummy (corresponding to the 35-44 age group) has a small and insignificant coefficient, while the second and third age dummies (corresponding to the 45-54 and 55-64 age groups) have coefficients that indicate declines in literacy skills of 2.4% and 4.3% respectively relative to the base category (the 26-35 age group). Once we include the cohort dummy variables, however, the age effects indicate a much steeper downward sloping profile, with the 45-54 year-olds having 6.8% lower literacy

12. The age categories in IALS differ by one year from those used to control for age in ALL and PIAAC. However, this small amount of measurement error makes little difference to our results. We estimated the same specifications as in Table 3a using only the pooled ALL and PIAAC data and obtained very similar results.

13. The key identifying assumption is that there are no interactions between the age and cohort effects. For example, this requires that cohorts that finish formal schooling with lower literacy do not lose their literacy as they age at a slower rate than cohorts that finish schooling with higher literacy.

levels and the 55-64 year-olds having 11.0% lower literacy than the base group (see column 4). Also, with the addition of cohort controls the 35-44 year-old age group now shows a statistically significant decline in literacy (of 2.6%) relative to the base group. At the same time, all the cohort dummies have positive effects that increase with the cohort (and in the specification including family background all are statistically significant, most at the 1% level). Cohort 1 (those aged 26-35 in 2003 and 35-44 in 2012), for example, has average literacy levels that are about 2% higher than those for the base cohort, which was 25-34 in 2012. The oldest cohorts have literacy levels that are about 9% higher than the base cohort. Overall, the implication from these results is that the small negative slope of the literacy-age profile (at least up to age 65) arises from a combination of literacy that declines with age at a greater rate than is suggested by the cross-sectional estimates and lower average literacy for more recent cohorts.

Do the ageing patterns observed in Canada also hold in other countries, or are they unique to Canadian society? We address this question using pooled IALS, ALL and PIAAC data in Tables A.3b to A.3f.[14] As noted previously, we chose these countries because they participated in all three rounds of international skills assessment. However, they also have the advantage of having a range of literacy levels and degrees of inequality in their literacy distributions. They also differ substantially in key determinants of literacy such as their education systems and the role of the family.

Tables A.3b and A.3c report estimates for the United States and Norway. Note that these estimates do not control for parents' education, which is not available in all three surveys for these countries. The patterns are similar to those for Canada. In the case of the United States, we again see declining literacy with age and the rate of decline is much steeper when we control for cohort effects (and similar in magnitude to that in Canada). The estimated coefficients associated with the cohort dummies are all positive, statistically significant, and increase monotonically from the youngest to oldest cohorts. In order to check that the U.S. results are not sensitive to the omission of controls for parents' education, we also estimated the same specifications using the pooled ALL and PIAAC samples which contain information on parents' education. The results are very similar, which is consistent with the estimates for Canada in Table A.3a that indicate that controlling for family background has little impact on the estimated relationship between literacy proficiency and age once cohort dummies are included (compare columns 2 and 4 in Table A.3a).

The same pattern is also evident – indeed, more pronounced -- in Norway. The rate at which skills fall with age is significantly greater in Norway than in Canada and the United States, with or without controlling for cohort effects. The estimated cohorts effects are all positive, statistically significant and increasing in size from the youngest to oldest cohorts. The cohort effects are also much larger than their counterparts in Canada and the United States, ranging from about 4% for the youngest cohort to 16% to 17% for the oldest (cohorts 4 and 5). Accordingly, our estimates indicate a steep decline in literacy with age in Norway, after controlling for differences in literacy across birth cohorts.

Table A.3d presents the same type of analysis for the Netherlands. There are noteworthy differences from the patterns found with the Canadian, U.S. and Norwegian data. In the Netherlands the estimated cohort effects are negative in sign, and are statistically significant when parental immigrant status is included as a control (parental education is not available in the Netherlands data). They are, however, small in size (most around -2%, with those for the oldest cohorts being -3%). As a consequence, the estimated relationship between literacy and age, controlling for cohort differences, is less pronounced than the cross-sectional estimates suggest but remains negative. Indeed, even with cohort controls included the partial relationship between literacy and age is quite steep in the Netherlands.

14. In the case of Italy it appears that ALL significantly understated the literacy proficiency of the adult population (Paccagnella, 2016). We therefore omit ALL and report results based on the pooled IALS and PIAAC samples.

Italy displays dramatically different behaviour than other countries. Without taking account of cohort differences there is no relationship between literacy and age in the Italian cross-sectional data. However, the estimated cohort effects are statistically significant, negative in sign and those for the older cohorts are large in size. Thus when cohort differences are taken into account there is a positive relationship between literacy and age. These results are inconsistent with other evidence about the relationship between literacy skills and age and warrant further investigation.

The results for Australia, which are based only on ALL and PIAAC and reported in Table A.3f, are similar to those for Canada and the United States. One small difference is that Australia is the only country in which cross-sectional estimates show some evidence of improvement in literacy with age relative to the base 25-34 year-old group (see columns 1 and 3). However, the difference in literacy between 35-39 and 40-44 year-olds and the base group is small (about 1%) and becomes insignificant once cohort dummies are included (see columns 2 and 4 of Table A.3f). At ages above 44, literacy declines at a rate similar to that in Canada and the United States, and lower than in Norway and the Netherlands. The pattern of the estimated cohort effects is also similar to that of Canada and the United States. As a consequence, when we compare columns 3 and 4 in Table A.3f we see the familiar result that the cross-sectional estimates of the relationship between literacy and age understate the true relationship.

Tables A.4a to A.4e contain estimated age and birth cohort effects for five countries that participated in IALS and PIAAC. Parental education is not available in the IALS data for these European countries, so controls for family background are limited to parental immigrant status. With the exception of Belgium, the cross-sectional literacy-age profile is steeper in these countries than in Australia, Canada and the United States (Belgium's cross-sectional profile is similar to Canada and the United States) Sweden and Ireland have particularly steep declines in literacy with age according to cross-sectional estimates, while the estimated profile in Denmark and Finland is similar to that in Norway and the Netherlands. Adding birth cohort dummies to the estimated relationship yields positive cohort effects that increase in size with older cohorts in Denmark, Ireland and Sweden. In these countries the extent to which literacy declines with age is understated in cross-sectional data. In contrast, the estimated cohort dummies in Finland and Belgium are negative in sign, although relatively small in size. In these countries the relationship between literacy and age is flatter once we control for differences in literacy across cohorts. Nonetheless, even after controlling for cohort differences there is a negative relationship between literacy proficiency and age in each of these countries. The extent to which literacy declines with age is particularly large in Ireland, Sweden and Denmark. In Belgium and Finland the estimated literacy-age profile is similar to that found for Canada and the United States.

5. Conclusion

The IALS, ALL and PIAAC surveys are unique in providing measures of basic literacy skills for representative samples of the adult population in participating countries. In this paper, we use these data to investigate the relationship between literacy skills and ageing in 11 OECD countries that participated in at least two of these surveys. Our cross-sectional analysis of the factors that influence literacy skills uses the PIAAC data for countries that participated in all three surveys: Australia, Canada, Italy, the Netherlands, Norway, and the United States. This analysis concludes that formal education is the primary driver of adult literacy skills. The characteristics of the respondents' parents –educational attainment and immigrant status – have significant effects on the respondents' education, but a direct impact on literacy that is relatively modest in size. Perhaps surprising is the general finding that literacy skills do not improve with age even over early phases of the adult life cycle. Rather, literacy proficiency shows little change from the mid-20s (after most individuals have completed formal schooling) to the mid-40s, and then declines. Taken at face value, these results suggest that literacy skills are primarily determined by formal schooling and to some extent by family background, and then decline with age, very gradually at first but at an increasing rate.

To investigate these issues further, we take advantage of the fact that the IALS, ALL and PIAAC surveys provide representative samples of the adult population at three points in time during the decades of the 1990s, 2000s and 2010s, which allows us to separately identify birth cohort and ageing effects. Doing so indicates that after controlling for cohort effects, literacy skills decline with age after completing formal schooling in all but one of these 11 countries. Italy is the sole exception to this common finding. We also find that in most of these OECD countries successive birth cohorts have poorer literacy outcomes – i.e. begin their adult lives with lower levels of literacy proficiency. The negative relationship between literacy skills and age found using cross-sectional data in most countries results from offsetting age and cohort effects. Once we control for cohort effects, the rate at which literacy proficiency falls with age is, in most countries, more pronounced, in some cases much more pronounced. In other words, the cross-sectional partial correlation between literacy and age understates the extent to which literacy declines with age. In contrast, in Finland, Italy and the Netherlands more recent cohorts have higher literacy than earlier birth cohorts. In these countries cross-sectional estimates overstate the rate at which literacy declines with age. In Finland and the Netherlands the estimated literacy improvement among more recent cohorts is modest in size, and the partial relationship between literacy and age remains strongly negative even after controlling for cohort effects. In Italy, however, the estimated improvement in literacy among more recent cohorts is so large that the implied partial relationship between literacy and age, controlling for cohort effects, is positive. Given the unexpected nature of this result, investigation of the reliability of the Italian data is warranted. Apart from the surprising Italian results, our analysis suggests that declining literacy with age is a pervasive phenomenon, but whether estimates of this relationship based on cross-sectional data under- or over-state this relationship varies across countries.

The rate at which literacy proficiency declines with age varies considerably across these OECD countries. Broadly speaking, countries fall into two main groups. Literacy falls moderately with age in Australia, Belgium, Canada, Finland, the Netherlands and the United States. For example, in this group the literacy skills of those age 55-64 are 8% to 11% lower than those age 25-34, controlling for other influences on skills. In Denmark, Ireland, Norway and Sweden literacy proficiency falls substantially with age – assessed skills of 55-64 year-olds are 18% to 23% below those of 25-34 year-olds. The reasons for these differences and their policy implications deserve attention.

There are also noteworthy differences across countries in the extent to which literacy skills are rising or falling across successive generations. In Finland, the Netherlands and Italy the estimated improvement in literacy across generations is relatively modest – gains between 1% and 2% for those born in the 1970s and 1980s relative to those born in the 1960s (1958-1967) and gains of 2% to 5% relative to those born in the 1950s (1948-1957). However, in the majority of countries literacy skills are falling across generations, in many cases at a more substantial rate. Belgium and Sweden show the smallest decline in literacy across birth cohorts – drops in literacy proficiency of 1% to 2% between those born in the 1960s and those born in the 1980s, and 2% to 4% between those born in the 1950s and those born in the 1980s. Ireland and Norway exhibit the greatest decline – decreases of 8% to 9% and 12 to 14% respectively across these birth cohorts. The remaining countries fall in between these extremes. Understanding the reasons for these changes in literacy proficiency across successive generations, and their policy implications, is an important issue for future research.

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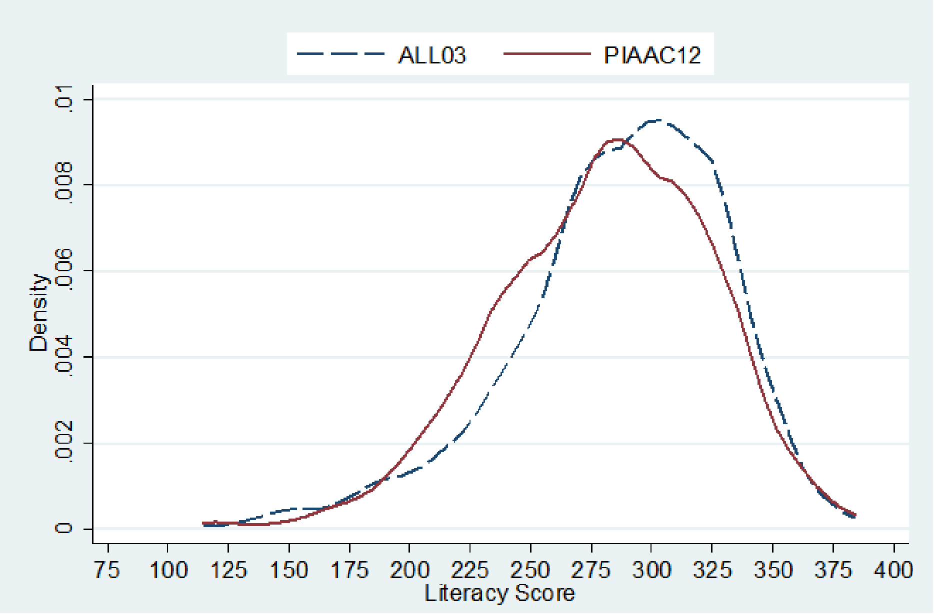
ANNEX A. SUPPORTING ANALYSIS

Distribution of literacy, Canada, PIAAC 2012 and ALL 2003

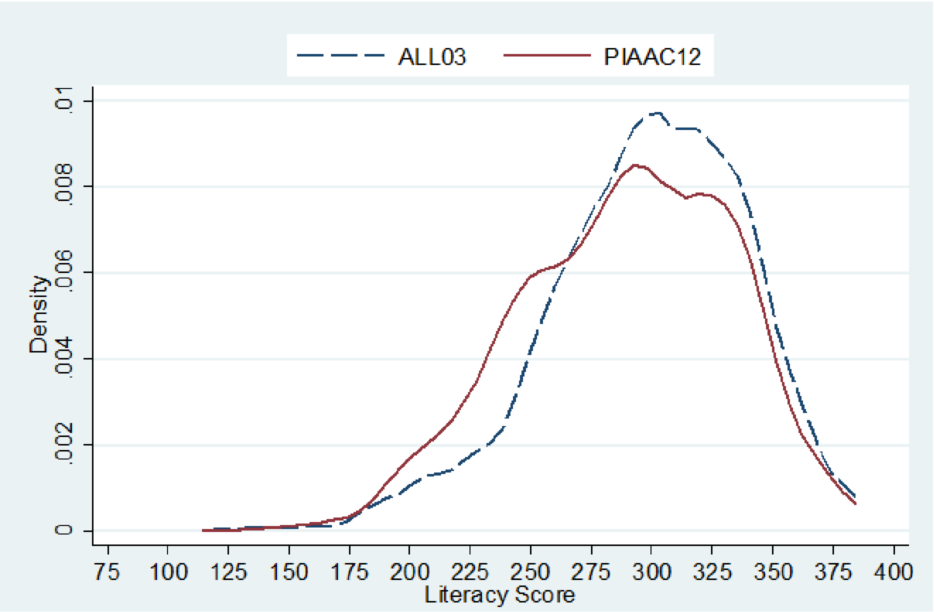
Figure A.1. Literacy in Canada, 2003 and 2012



Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

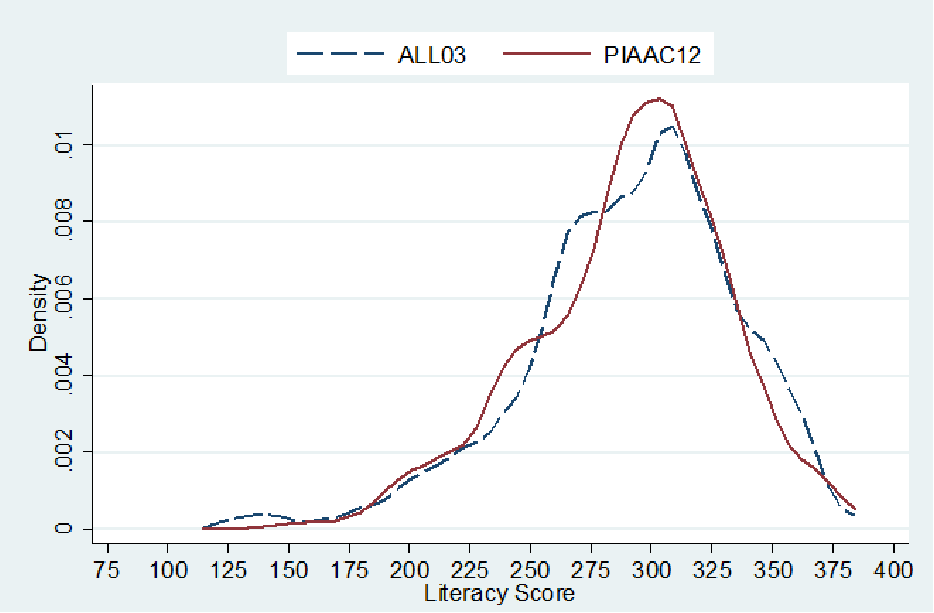
Distribution of literacy by age group, Canada, PIAAC 2012 and ALL 2003

Figure A.2. Literacy in Canada, age 25-34



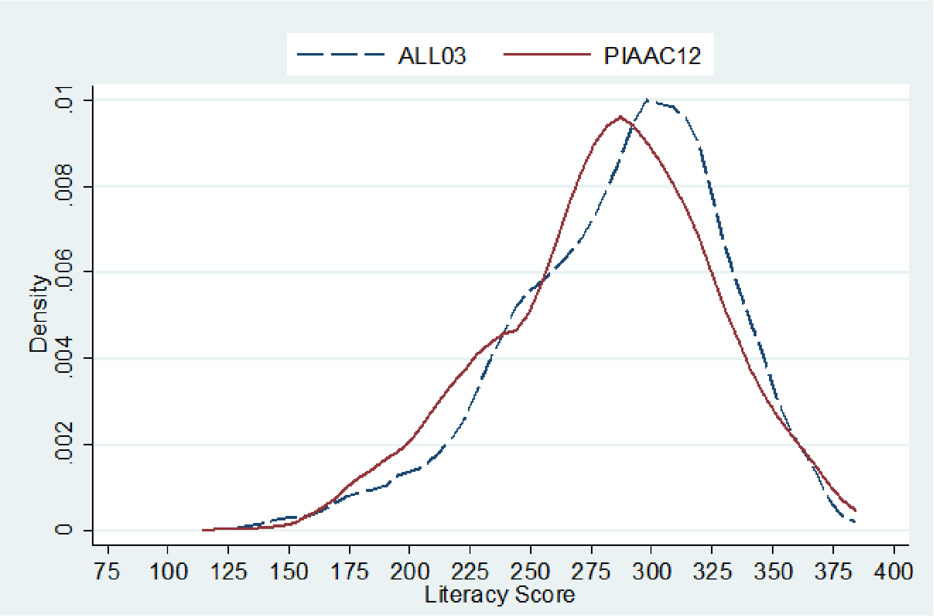
Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Figure A.3. Literacy in Canada, age 35-44



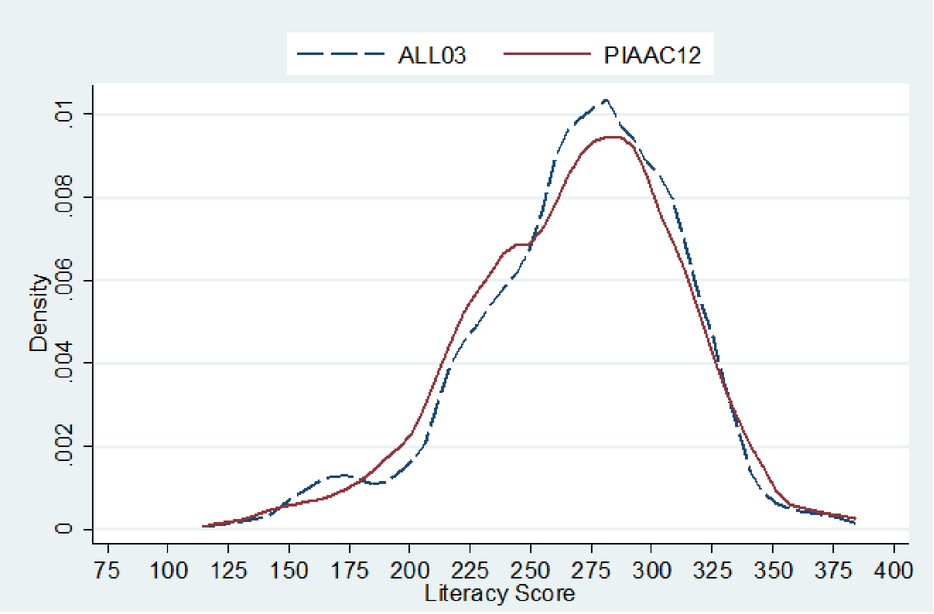
Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Figure A.4. Literacy in Canada, age 45-54



Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

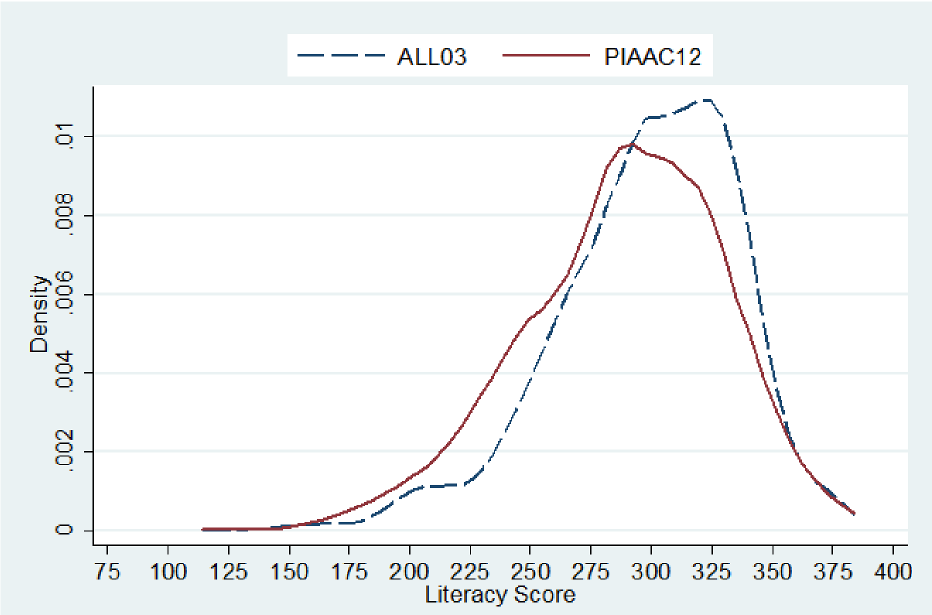
Figure A.5. Literacy in Canada, age 55-64



Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

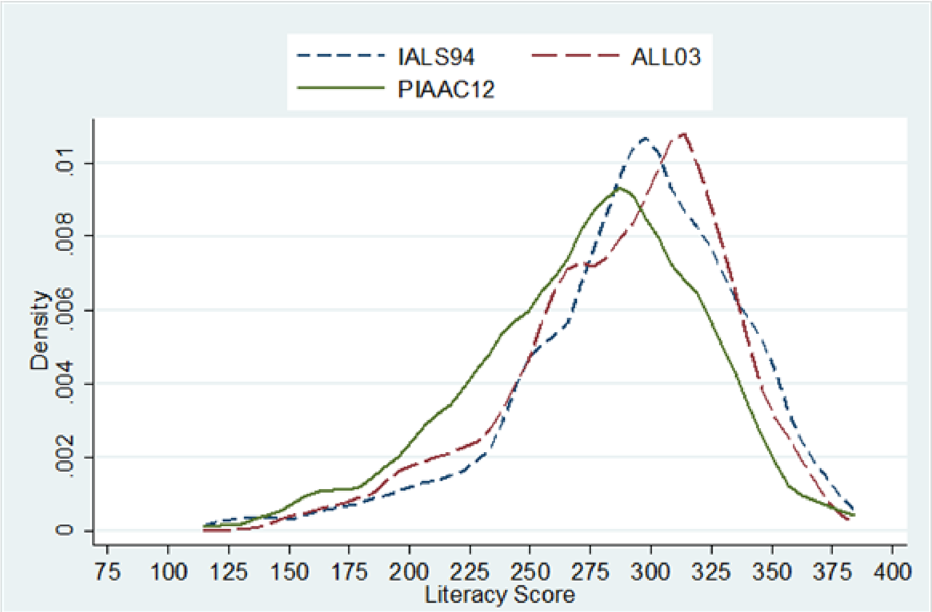
Distribution of literacy by birth cohort, Canada, PIAAC 2012 - ALL 2003 – IALS 1994

Figure A.6. Literacy in Canada, 16-25 in 1994



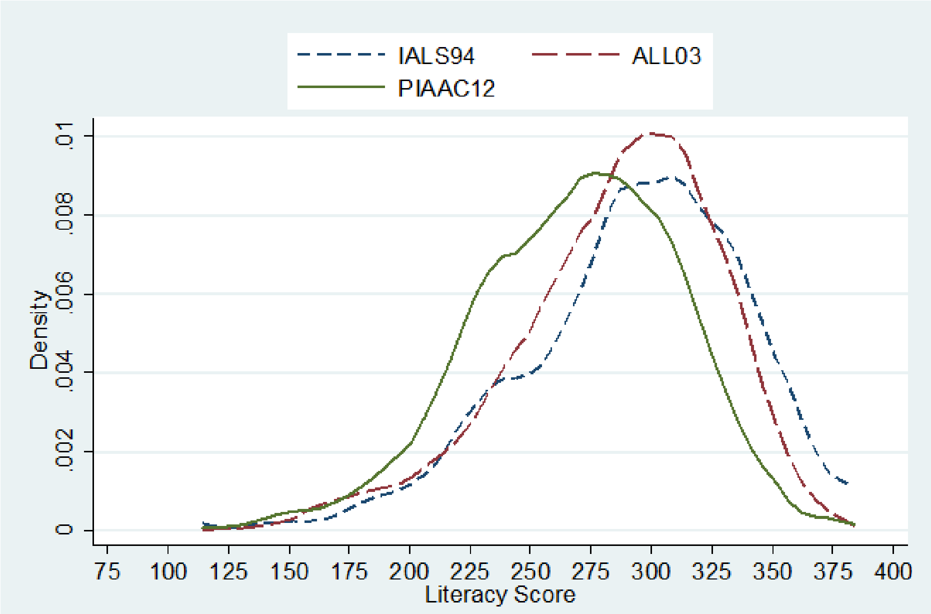
Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Figure A.7. Literacy in Canada, 26-35 in 1994



Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Figure A.8. Literacy in Canada, 36-45 in 1994



Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.1. Summary statistics, Canada

	PIAAC	ALL	IALS
Literacy	270.593	274.489	268.362
Female	0.5411	0.553	0.565
Years of schooling	13.694	12.731	11.720
Years of schooling squared	252.981	174.798	149.155
Education - level of attainment			
Less than high school	0.1593	0.2586	0.3944
High school	0.2158	0.2991	0.2840
Above high school	-	0.4423	-
Some post secondary	0.4061	-	0.1848
University degree	0.2188	-	0.1247
Age of respondent			
Age: 25-34	0.1979	0.2101	0.3142
Age: 35-44	0.2247	0.2911	0.3125
Age: 45-54	0.2908	0.2907	0.2019
Age: 55-64	0.2866	0.2081	0.1714
Mother's education			
ISCED1,2,3(short)	0.4476	0.5543	0.6033
ISCED 3(long), 4	0.3165	0.2325	0.2223

Table A.1. Summary statistics, Canada (*continued*)

	PIAAC	ALL	IALS
ISCED5,6	0.1818	0.1303	0.0245
None reported	0.0541	0.0829	0.1599
Father's education			
ISCED1,2,3(short)	0.4815	0.5854	0.6298
ISCED 3(long), 4	0.2884	0.1965	0.1506
ISCED5,6	0.1568	0.1119	0.0443
None reported	0.0733	0.1062	0.1754
Parental immigration			
Immigrant mother	0.0684	0.0681	0.0741
Immigrant father	0.0799	0.0861	0.0848
Cohort age in PIAAC			
Cohort 0 25-34	0.1979	-	-
Cohort 1 35-44	0.2247	0.2101	-
Cohort 2 45-54	0.2908	0.2911	0.3142
Cohort 3 55-64	0.2866	0.2907	0.3125
Cohort 4 55-64 in ALL	-	0.2081	0.2019
Cohort 5 55-64 in IALS	-	-	0.1714
Observations	17 898	13 464	2 982

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.2a. Regression results, Canada, PIAAC Survey

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0090***	-0.0070**	-0.0071**	-0.0101***	-0.0079**	-0.0080**
	[0.003]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]
Years of schooling	0.0472***	0.0414***	0.0413***			
	[0.001]	[0.001]	[0.001]			
Years of schooling squared	-0.0005***	-0.0004***	-0.0004***			
	[0.000]	[0.000]	[0.000]			
Own education						
Less than high school				-0.1715***	-0.1511***	-0.1510***
				[0.008]	[0.008]	[0.008]
Some post secondary				0.0354***	0.0315***	0.0311***
				[0.005]	[0.005]	[0.005]
University degree				0.1436***	0.1236***	0.1234***
				[0.005]	[0.005]	[0.005]
Age of respondent (10-year bands)						
Age: 35-44	-0.0129***	-0.0033		-0.0127**	-0.0029	
	[0.005]	[0.005]		[0.005]	[0.005]	
Age: 45-54	-0.0422***	-0.0250***		-0.0402***	-0.0228***	
	[0.005]	[0.005]		[0.005]	[0.005]	
Age: 55-64	-0.0569***	-0.0333***		-0.0582***	-0.0338***	
	[0.005]	[0.005]		[0.005]	[0.005]	
Age of respondent (5-year bands)						
Age: 35-39			-0.0001			0.0014
			[0.006]			[0.006]
Age: 40-44			-0.0066			-0.0071
			[0.006]			[0.006]
Age: 45-49			-0.0202***			-0.0182***
			[0.007]			[0.007]
Age: 50-54			-0.0296***			-0.0272***
			[0.006]			[0.006]
Age: 55-59			-0.0301***			-0.0305***
			[0.006]			[0.006]
Age: 60-64			-0.0374***			-0.0379***
			[0.006]			[0.006]
Mother's education						
ISCED1,2,3 (short)		-0.0322***	-0.0318***		-0.0328***	-0.0324***
		[0.004]	[0.004]		[0.004]	[0.004]
ISCED5,6		0.0074	0.0075		0.0081*	0.0082*
		[0.005]	[0.005]		[0.005]	[0.005]
None reported		-0.0649***	-0.0643***		-0.0655***	-0.0650***
		[0.011]	[0.011]		[0.011]	[0.011]
Father's education						
ISCED1,2,3 (short)		-0.0097**	-0.0094**		-0.0096**	-0.0093**
		[0.004]	[0.004]		[0.004]	[0.004]
ISCED5,6		0.0135***	0.0133***		0.0155***	0.0153***

Table A.2a. Regression results, Canada, PIAAC Survey (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
		[0.005]	[0.005]		[0.005]	[0.005]
None reported		-0.0656***	-0.0657***		-0.0637***	-0.0639***
		[0.009]	[0.009]		[0.009]	[0.009]
Parental immigration						
Immigrant mother		0.0096	0.0098		0.0095	0.0098
		[0.007]	[0.007]		[0.007]	[0.007]
Immigrant father		0.0053	0.0053		0.0075	0.0074
		[0.006]	[0.006]		[0.006]	[0.006]
Constant	5.1093***	5.1792***	5.1797***	5.6245***	5.6295***	5.6296***
	[0.013]	[0.014]	[0.014]	[0.005]	[0.006]	[0.006]
Observations	17 898	17 898	17 898	17 898	17 898	17 898
R-squared	0.333	0.361	0.362	0.323	0.352	0.352

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2b. Regression results, United States, PIAAC Survey

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0107**	-0.0054	-0.0054	-0.0112**	-0.0054	-0.0054
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Years of schooling	0.0501***	0.0412***	0.0411***			
	[0.001]	[0.002]	[0.002]			
Years of schooling squared	-0.0004***	-0.0004***	-0.0004***			
	[0.000]	[0.000]	[0.000]			
Own education						
Less than high school				-0.1604***	-0.1263***	-0.1263***
				[0.012]	[0.012]	[0.012]
Some post secondary				0.0578***	0.0476***	0.0477***
				[0.008]	[0.007]	[0.007]
University degree				0.1633***	0.1299***	0.1295***
				[0.006]	[0.006]	[0.006]
Age of respondent (10-year bands)						
Age: 35-44	-0.0077	-0.0067		-0.0107	-0.0081	
	[0.007]	[0.007]		[0.007]	[0.007]	
Age: 45-54	-0.0233***	-0.0154**		-0.0261***	-0.0156**	
	[0.008]	[0.007]		[0.008]	[0.008]	
Age: 55-64	-0.0473***	-0.0290***		-0.0462***	-0.0246***	
	[0.008]	[0.007]		[0.008]	[0.008]	
Age of respondent (5-year bands)			-0.0044			-0.0056
Age: 35-39			[0.009]			[0.009]
			-0.0088			-0.0105
Age: 40-44			[0.009]			[0.009]
			-0.0167*			-0.0170*

Table A.2b. Regression results, United States, PIAAC Survey (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Age: 45-49			[0.009]			[0.009]
			-0.0139			-0.0139
Age: 50-54			[0.009]			[0.009]
			-0.0360***			-0.0328***
Age: 55-59			[0.009]			[0.010]
			-0.0223**			-0.0168*
Age: 60-64			[0.009]			[0.009]
Mother's education						
ISCED1,2,3(short)		-0.0381***	-0.0386***		-0.0398***	-0.0404***
		[0.008]	[0.008]		[0.008]	[0.008]
ISCED5,6		0.0085	0.0085		0.0146**	0.0146**
		[0.007]	[0.007]		[0.007]	[0.007]
None reported		-0.0561**	-0.0567**		-0.0652**	-0.0658**
		[0.029]	[0.028]		[0.031]	[0.031]
Father's education						
ISCED1,2,3(short)		-0.0361***	-0.0365***		-0.0401***	-0.0405***
		[0.008]	[0.008]		[0.008]	[0.008]
ISCED5,6		0.0227***	0.0228***		0.0237***	0.0239***
		[0.007]	[0.007]		[0.007]	[0.007]
None reported		-0.0850***	-0.0854***		-0.0900***	-0.0904***
		[0.016]	[0.016]		[0.017]	[0.017]
Parental immigration						
Immigrant mother		-0.0095	-0.0094		-0.0018	-0.0017
		[0.014]	[0.014]		[0.015]	[0.015]
Immigrant father		-0.0079	-0.0075		-0.0056	-0.0052
		[0.012]	[0.012]		[0.013]	[0.013]
Constant	5.0218***	5.1352***	5.1362***	5.5811***	5.5934***	5.5936***
	[0.018]	[0.020]	[0.020]	[0.008]	[0.008]	[0.008]
Observations	3 513	3 513	3 513	3 513	3 513	3 513
R-squared	0.329	0.371	0.372	0.295	0.345	0.346

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2c. Regression results, Norway, PIAAC Survey

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0188***	-0.0178***	-0.0177***	-0.0235***	-0.0221***	-0.0220***
	[0.005]	[0.004]	[0.004]	[0.005]	[0.004]	[0.004]
Years of schooling	0.0350***	0.0311***	0.0309***			
	[0.001]	[0.002]	[0.002]			
Years of schooling squared	-0.0003***	-0.0003***	-0.0003***			
	[0.000]	[0.000]	[0.000]			
Own education						
Less than high school				-0.0441***	-0.0395***	-0.0390***
				[0.008]	[0.008]	[0.008]
Some post secondary				0.0375***	0.0321***	0.0323***
				[0.007]	[0.007]	[0.007]
University degree				0.1189***	0.1062***	0.1060***
				[0.005]	[0.005]	[0.005]
Age of respondent (10-year bands)						
Age: 35-44	-0.0178***	-0.0084		-0.0172***	-0.0080	
	[0.006]	[0.006]		[0.006]	[0.006]	
Age: 45-54	-0.0529***	-0.0379***		-0.0515***	-0.0368***	
	[0.006]	[0.006]		[0.006]	[0.006]	
Age: 55-64	-0.1116***	-0.0930***		-0.1136***	-0.0950***	
	[0.007]	[0.007]		[0.007]	[0.007]	
Age of respondent (5-year bands)						
Age: 35-39			-0.0058			-0.0076
			[0.007]			[0.007]
Age: 40-44			-0.0115			-0.0091
			[0.007]			[0.007]
Age: 45-49			-0.0262***			-0.0258***
			[0.007]			[0.007]
Age: 50-54			-0.0517***			-0.0497***
			[0.008]			[0.008]
Age: 55-59			-0.0817***			-0.0824***
			[0.009]			[0.009]
Age: 60-64			-0.1040***			-0.1071***
			[0.009]			[0.009]
Mother's education						
ISCED1,2,3(short)		-0.0163***	-0.0144***		-0.0173***	-0.0155***
		[0.006]	[0.006]		[0.005]	[0.006]
ISCED5,6		0.0145**	0.0151**		0.0117*	0.0123**
		[0.006]	[0.006]		[0.006]	[0.006]
None reported		-0.1198***	-0.1179***		-0.1336***	-0.1319***
		[0.038]	[0.038]		[0.039]	[0.039]
Father's education						
ISCED1,2,3(short)		-0.0167***	-0.0164***		-0.0161***	-0.0157***
		[0.006]	[0.006]		[0.006]	[0.006]
ISCED5,6		0.0144***	0.0139**		0.0143***	0.0139**
		[0.005]	[0.005]		[0.005]	[0.005]

Table A.2c. Regression results, Norway, PIAAC Survey (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
None reported		-0.0249	-0.0240		-0.0260	-0.0254
		[0.035]	[0.034]		[0.035]	[0.035]
Parental immigration						
Immigrant mother		-0.0066	-0.0065		-0.0082	-0.0080
		[0.014]	[0.014]		[0.015]	[0.015]
Immigrant father		-0.0359*	-0.0363*		-0.0380*	-0.0383*
		[0.019]	[0.019]		[0.020]	[0.020]
Constant	5.2559***	5.3051***	5.3065***	5.6618***	5.6672***	5.6666***
	[0.020]	[0.021]	[0.021]	[0.006]	[0.007]	[0.007]
Observations	3 431	3 431	3 431	3 431	3 431	3 431
R-squared	0.311	0.330	0.334	0.312	0.332	0.335

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.
Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2d. Regression results, the Netherlands, PIAAC Survey

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0170***	-0.0181***	-0.0181***	-0.0162***	-0.0172***	-0.0172***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Years of schooling	0.0400***	0.0364***	0.0363***			
	[0.001]	[0.002]	[0.002]			
Years of schooling squared	-0.0004***	-0.0003***	-0.0003***			
	[0.000]	[0.000]	[0.000]			
Own education						
Less than high school				-0.1033***	-0.0972***	-0.0954***
				[0.007]	[0.007]	[0.007]
Some post secondary				0.0390***	0.0331***	0.0341***
				[0.009]	[0.009]	[0.009]
University degree				0.0985***	0.0881***	0.0892***
				[0.004]	[0.004]	[0.004]
Age of respondent (10-year bands)						
Age: 35-44	-0.0021	0.0008		-0.0030	-0.0006	
	[0.006]	[0.006]		[0.006]	[0.006]	
Age: 45-54	-0.0450***	-0.0396***		-0.0450***	-0.0406***	
	[0.006]	[0.006]		[0.006]	[0.006]	
Age: 55-64	-0.0997***	-0.0929***		-0.0998***	-0.0937***	
	[0.007]	[0.007]		[0.007]	[0.007]	
Age of respondent (5-year bands)						
Age: 35-39			0.0006			-0.0013
			[0.007]			[0.007]
Age: 40-44			0.0005			-0.0006
			[0.007]			[0.007]

Table A.2d. Regression results, the Netherlands, PIAAC Survey (continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Age: 45-49			-0.0244***			-0.0242***
			[0.007]			[0.007]
Age: 50-54			-0.0566***			-0.0590***
			[0.008]			[0.008]
Age: 55-59			-0.0790***			-0.0813***
			[0.008]			[0.008]
Age: 60-64			-0.1048***			-0.1049***
			[0.008]			[0.008]
Mother's education						
ISCED1,2,3(short)		-0.0182***	-0.0172***		-0.0156***	-0.0146**
		[0.006]	[0.006]		[0.006]	[0.006]
ISCED5,6		0.0076	0.0083		0.0081	0.0085
		[0.008]	[0.008]		[0.008]	[0.008]
None reported		-0.0775**	-0.0779**		-0.0922**	-0.0922**
		[0.039]	[0.039]		[0.037]	[0.037]
Father's education						
ISCED1,2,3(short)		-0.0196***	-0.0192***		-0.0184***	-0.0180***
		[0.006]	[0.006]		[0.006]	[0.006]
ISCED5,6		0.0080	0.0080		0.0062	0.0060
		[0.006]	[0.006]		[0.006]	[0.006]
None reported		-0.0764***	-0.0759***		-0.0860***	-0.0858***
		[0.027]	[0.028]		[0.026]	[0.026]
Parental immigration						
Immigrant mother		-0.0209*	-0.0226*		-0.0189	-0.0206*
		[0.012]	[0.012]		[0.012]	[0.012]
Immigrant father		-0.0385***	-0.0375***		-0.0407***	-0.0397***
		[0.013]	[0.013]		[0.013]	[0.013]
Constant	5.2270***	5.2928***	5.2935***	5.6936***	5.7182***	5.7168***
	[0.019]	[0.021]	[0.021]	[0.006]	[0.007]	[0.007]
Observations	3 786	3 786	3 786	3 786	3 786	3 786
R-squared	0.369	0.389	0.393	0.366	0.386	0.391

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2e. Regression results, Italy, PIAAC Survey

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0055	0.0072	0.0071	-0.0011	0.0009	0.0006
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Years of schooling	0.0566***	0.0580***	0.0579***			
	[0.004]	[0.004]	[0.004]			
Years of schooling squared	-0.0015***	-0.0017***	-0.0017***			
	[0.000]	[0.000]	[0.000]			
Own education						
Less than high school				-0.1255***	-0.1171***	-0.1171***
				[0.006]	[0.006]	[0.006]
Some post secondary				0.0361*	0.0360*	0.0364*
				[0.022]	[0.020]	[0.020]
University degree				0.0597***	0.0458***	0.0455***
				[0.007]	[0.008]	[0.008]
Age of respondent (10-year bands)						
Age: 35-44	0.0028	0.0067		0.0017	0.0057	
	[0.008]	[0.008]		[0.008]	[0.008]	
Age: 45-54	0.0026	0.0094		-0.0020	0.0051	
	[0.008]	[0.008]		[0.008]	[0.009]	
Age: 55-64	-0.0260***	-0.0188**		-0.0587***	-0.0510***	
	[0.009]	[0.009]		[0.009]	[0.009]	
Age of respondent (5-year bands)						
Age: 35-39			0.0019			0.0003
			[0.009]			[0.009]
Age: 40-44			0.0114			0.0107
			[0.009]			[0.009]
Age: 45-49			0.0071			0.0022
			[0.010]			[0.010]
Age: 50-54			0.0124			0.0085
			[0.010]			[0.011]
Age: 55-59			-0.0168			-0.0365***
			[0.012]			[0.013]
Age: 60-64			-0.0199*			-0.0604***
			[0.011]			[0.011]
Mother's education						
ISCED1,2,3(short)		-0.0203**	-0.0202**		-0.0185**	-0.0185**
		[0.009]	[0.009]		[0.009]	[0.009]
ISCED5,6		0.0264*	0.0265*		0.0201	0.0203
		[0.015]	[0.015]		[0.016]	[0.016]
None reported		-0.0647	-0.0660		-0.0671	-0.0665
		[0.065]	[0.065]		[0.060]	[0.060]
Father's education						
ISCED1,2,3(short)		-0.0261***	-0.0265***		-0.0314***	-0.0317***
		[0.008]	[0.008]		[0.008]	[0.008]
ISCED5,6		-0.0162	-0.0161		-0.0181	-0.0179
		[0.014]	[0.014]		[0.014]	[0.014]

Table A.2e. Regression results, Italy, PIAAC Survey (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
None reported		-0.0866	-0.0842		-0.0995*	-0.0977
		[0.056]	[0.057]		[0.060]	[0.060]
Parental immigration						
Immigrant mother		0.0392**	0.0394**		0.0460**	0.0456**
		[0.020]	[0.020]		[0.020]	[0.020]
Immigrant father		-0.0736**	-0.0748***		-0.0712**	-0.0744**
		[0.029]	[0.029]		[0.030]	[0.030]
Constant	5.1094***	5.1455***	5.1460***	5.5832***	5.6171***	5.6175***
	[0.026]	[0.028]	[0.029]	[0.007]	[0.010]	[0.010]
Observations	3 678	3 678	3 678	3 678	3 678	3 678
R-squared	0.294	0.304	0.304	0.242	0.253	0.254

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2f. Regression results, Australia, PIAAC Survey

Variables	(1)	(2)	(3)
Female	-0.0090*	-0.0065	-0.0066
	[0.005]	[0.005]	[0.005]
Own education			
Less than high school	-0.2375***	-0.2121***	-0.2115***
	[0.029]	[0.028]	[0.028]
Some post secondary	0.0429***	0.0350***	0.0346***
	[0.006]	[0.006]	[0.006]
University degree	0.1619***	0.1337***	0.1343***
	[0.006]	[0.006]	[0.006]
Age of respondent (10-year bands)			
Age: 35-44	-0.0065	-0.0027	
	[0.007]	[0.006]	
Age: 45-54	-0.0347***	-0.0245***	
	[0.007]	[0.007]	
Age: 55-64	-0.0586***	-0.0446***	
	[0.008]	[0.009]	
Age of respondent (5-year bands)			
Age: 35-39			0.0034
			[0.008]
Age: 40-44			-0.0096
			[0.008]
Age: 45-49			-0.0131
			[0.009]
Age: 50-54			-0.0371***
			[0.009]

Table A.2f. Regression results, Australia, PIAAC Survey (*continued*)

Variables	(1)	(2)	(3)
Age: 55-59			-0.0467***
			[0.011]
Age: 60-64			-0.0431***
			[0.010]
Mother's education			
Less than high school		-0.0373***	-0.0365***
		[0.008]	[0.008]
Some post secondary		0.0030	0.0022
		[0.008]	[0.008]
University degree		0.0156*	0.0149*
		[0.009]	[0.009]
None reported		-0.0760***	-0.0755***
		[0.013]	[0.013]
Father's education			
Less than high school		-0.0055	-0.0053
		[0.008]	[0.008]
Some post secondary		0.0117*	0.0124*
		[0.007]	[0.007]
University degree		0.0257***	0.0245***
		[0.008]	[0.008]
None reported		-0.0569***	-0.0567***
		[0.012]	[0.012]
Parental immigration			
Immigrant mother		-0.0307***	-0.0309***
		[0.009]	[0.009]
Immigrant father		0.0145*	0.0139*
		[0.008]	[0.008]
Constant	5.6192***	5.6402***	5.6405***
	[0.007]	[0.007]	[0.007]
Observations	4 426	4 426	4 426
R-squared	0.2507	0.3064	0.3082

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.3a. Regression results, Canada, IALS, ALL and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	0.0034	0.0034	0.0049*	0.0050*
	[0.003]	[0.003]	[0.003]	[0.003]
Years of schooling	0.0443***	0.0445***	0.0402***	0.0399***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0122***	-0.0240***	-0.0046	-0.0259***
	[0.004]	[0.005]	[0.004]	[0.005]
Age: 45-54	-0.0369***	-0.0632***	-0.0244***	-0.0682***
	[0.004]	[0.007]	[0.004]	[0.007]
Age: 55-64	-0.0584***	-0.1014***	-0.0428***	-0.1099***
	[0.004]	[0.009]	[0.004]	[0.010]
Mother's education				
ISCED1,2,3(short)			-0.0291***	-0.0322***
			[0.003]	[0.003]
ISCED5,6			0.0004	0.0031
			[0.004]	[0.004]
None reported			-0.0474***	-0.0538***
			[0.008]	[0.008]
Father's education				
ISCED1,2,3(short)			-0.0125***	-0.0163***
			[0.003]	[0.003]
ISCED5,6			0.0052	0.0059
			[0.004]	[0.004]
None reported			-0.0448***	-0.0506***
			[0.007]	[0.007]
Parental immigration				
Immigrant mother			0.0088	0.0091*
			[0.005]	[0.005]
Immigrant father			0.0067	0.0073
			[0.005]	[0.005]
Cohort				
Cohort 1		0.0093*		0.0202***
		[0.006]		[0.006]
Cohort 2		0.0200***		0.0418***
		[0.007]		[0.007]
Cohort 3		0.0455***		0.0769***
		[0.008]		[0.009]
Cohort 4		0.0556***		0.0934***
		[0.013]		[0.014]

Table A.3a. Regression results, Canada, IALS, ALL and PIAAC pooled (*continued*)

Variables	(1)	(2)	(3)	(4)
Cohort 5		0.0522		0.0892**
		[0.038]		[0.039]
Constant	5.1451***	5.1360***	5.2072***	5.1958***
	[0.016]	[0.015]	[0.018]	[0.017]
Observations	34 308	34 308	34 308	34 308
R-squared	0.337	0.339	0.354	0.358

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.3b. Regression results, United States, IALS, ALL and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	0.0064*	0.0059	0.0062	0.0057
	[0.004]	[0.004]	[0.004]	[0.004]
Years of schooling	0.0479***	0.0481***	0.0479***	0.0482***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0088*	-0.0268***	-0.0097*	-0.0264***
	[0.005]	[0.006]	[0.005]	[0.006]
Age: 45-54	-0.0254***	-0.0595***	-0.0270***	-0.0594***
	[0.005]	[0.007]	[0.005]	[0.007]
Age: 55-64	-0.0530***	-0.1066***	-0.0543***	-0.1067***
	[0.005]	[0.009]	[0.005]	[0.009]
Parental immigration				
Immigrant mother			-0.0166*	-0.0170*
			[0.009]	[0.009]
Immigrant father			-0.0293***	-0.0293***
			[0.009]	[0.009]
Cohort				
Cohort 1		0.0171**		0.0155**
		[0.007]		[0.007]
Cohort 2		0.0338***		0.0308***
		[0.008]		[0.008]
Cohort 3		0.0514***		0.0479***
		[0.010]		[0.010]
Cohort 4		0.0710***		0.0688***
		[0.011]		[0.011]
Cohort 5		0.0974***		0.0972***
		[0.014]		[0.014]
Constant	5.0545***	5.0373***	5.0572***	5.0411***
	[0.014]	[0.015]	[0.014]	[0.015]
Observations	7 758	7 758	7 758	7 758
R-squared	0.330	0.337	0.333	0.339

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.3c. Regression results, Norway, IALS, ALL and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0073**	-0.0073***	-0.0074**	-0.0074***
	[0.003]	[0.003]	[0.003]	[0.003]
Years of schooling	0.0244***	0.0282***	0.0246***	0.0282***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0115***	-0.0542***	-0.0119***	-0.0540***
	[0.004]	[0.005]	[0.004]	[0.005]
Age: 45-54	-0.0520***	-0.1333***	-0.0525***	-0.1329***
	[0.004]	[0.006]	[0.004]	[0.006]
Age: 55-64	-0.1130***	-0.2314***	-0.1134***	-0.2308***
	[0.004]	[0.008]	[0.004]	[0.008]
Parental immigration				
Immigrant mother			-0.0173	-0.0090
			[0.011]	[0.011]
Immigrant father			-0.0239*	-0.0162
			[0.014]	[0.014]
Cohort				
Cohort 1		0.0402***		0.0394***
		[0.006]		[0.006]
Cohort 2		0.0911***		0.0900***
		[0.007]		[0.007]
Cohort 3		0.1274***		0.1261***
		[0.008]		[0.008]
Cohort 4		0.1775***		0.1760***
		[0.010]		[0.010]
Cohort 5		0.1624***		0.1606***
		[0.016]		[0.016]
		[0.012]		[0.012]
Constant	5.4279***	5.3444***	5.4277***	5.3453***
	[0.009]	[0.011]	[0.009]	[0.011]
Observations	9 963	9 963	9 963	9 963
R-squared	0.278	0.306	0.279	0.306

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.3d. Regression results, the Netherlands, IALS, ALL and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0068**	-0.0070**	-0.0067**	-0.0070**
	[0.003]	[0.003]	[0.003]	[0.003]
Years of schooling	0.0253***	0.0252***	0.0254***	0.0253***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0002***	-0.0002***	-0.0003***	-0.0002***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0110***	-0.0109**	-0.0124***	-0.0112***
	[0.004]	[0.004]	[0.004]	[0.004]
Age: 45-54	-0.0485***	-0.0454***	-0.0497***	-0.0452***
	[0.004]	[0.006]	[0.004]	[0.006]
Age: 55-64	-0.0960***	-0.0854***	-0.0977***	-0.0856***
	[0.004]	[0.008]	[0.004]	[0.008]
Parental immigration				
Immigrant mother			-0.0162**	-0.0171**
			[0.008]	[0.008]
Immigrant father			-0.0295***	-0.0293***
			[0.010]	[0.010]
Cohort				
Cohort 1		-0.0193**		-0.0205***
		[0.008]		[0.008]
Cohort 2		-0.0137		-0.0165**
		[0.009]		[0.008]
Cohort 3		-0.0188**		-0.0217**
		[0.009]		[0.009]
Cohort 4		-0.0280**		-0.0311***
		[0.011]		[0.011]
Cohort 5		-0.0282**		-0.0309**
		[0.013]		[0.013]
Constant	5.3927***	5.4092***	5.3947***	5.4128***
	[0.011]	[0.012]	[0.011]	[0.012]
Observations	9 980	9 980	9 980	9 980
R-squared	0.305	0.306	0.308	0.309

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.3e. Regression results, Italy, IALS and PIAAC only pooled

Variables	(1)	(2)	(3)	(4)
Female	0.0030	0.0030	0.0030	0.0029
	[0.006]	[0.006]	[0.006]	[0.006]
Years of schooling	0.0894***	0.0865***	0.0894***	0.0865***
	[0.005]	[0.005]	[0.005]	[0.005]
Years of schooling squared	-0.0027***	-0.0026***	-0.0027***	-0.0026***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0075	-0.0016	-0.0076	-0.0018
	[0.008]	[0.008]	[0.008]	[0.008]
Age: 45-54	-0.0083	0.0174*	-0.0082	0.0173*
	[0.008]	[0.010]	[0.008]	[0.010]
Age: 55-64	-0.0098	0.0358***	-0.0100	0.0354**
	[0.010]	[0.014]	[0.010]	[0.014]
Parental immigration				
Immigrant mother			0.0370	0.0341
			[0.023]	[0.023]
Immigrant father			-0.0223	-0.0234
			[0.024]	[0.024]
Cohort				
Cohort 2		-0.0162*		-0.0160*
		[0.009]		[0.009]
Cohort 3		-0.0415***		-0.0411***
		[0.011]		[0.011]
Cohort 4		-0.0687***		-0.0685***
		[0.013]		[0.013]
Constant	4.9015***	4.9260***	4.9017***	4.9262***
	[0.032]	[0.031]	[0.032]	[0.031]
Observations	5 376	5 376	5 376	5 376
R-squared	0.354	0.359	0.354	0.360

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.3f. Regression results, Australia, ALL and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	0.0139***	0.0139***	0.0146***	0.0149***
	[0.004]	[0.004]	[0.004]	[0.004]
Own education				
Less than high school	-0.2293***	-0.2309***	-0.2100***	-0.2112***
	[0.016]	[0.016]	[0.016]	[0.016]
Some post secondary	0.0445***	0.0443***	0.0382***	0.0379***
	[0.0054]	[0.0054]	[0.004]	[0.004]
University degree	0.1632***	0.1631***	0.1374	0.1367
	[0.004]	[0.004]	[0.004]	[0.004]
Age of respondent (5-year bands)				
Age: 35-39	0.0091*	0.0103	0.0149***	0.0080
	[0.005]	[0.008]	[0.005]	[0.008]
Age: 40-44	0.0026	-0.0023	0.0121**	-0.0041
	[0.006]	[0.012]	[0.006]	[0.010]
Age: 45-49	-0.0098	-0.0280*	0.0030	-0.0230*
	[0.007]	[0.012]	[0.007]	[0.012]
Age: 50-54	-0.0243***	-0.0637***	-0.0090	-0.0477***
	[0.007]	[0.019]	[0.007]	[0.015]
Age: 55-59	-0.0347***	-0.0959***	-0.0174**	-0.0717***
	[0.007]	[0.023]	[0.007]	[0.012]
Age: 60-64	-0.0604***	-0.1264***	-0.0370***	-0.0980***
	[0.007]	[0.026]	[0.008]	[0.020]
Mother's education				
Less than high school			-0.0458***	-0.0474***
			[0.005]	[0.005]
Some post secondary			0.0059	0.0079
			[0.007]	[0.007]
University degree			0.0162**	0.0163**
			[0.007]	[0.007]
None reported			-0.0768***	-0.0759***
			[0.013]	[0.012]
Father's education				
Less than high school			-0.0169***	-0.0187***
			[0.005]	[0.005]
Some post secondary			0.0105*	0.0127*
			[0.006]	[0.006]
University degree			0.0162***	0.0159***
			[0.006]	[0.006]
None reported			-0.0628***	-0.0616***
			[0.012]	[0.012]

Table A.3f. Regression results, Australia, ALL and PIAAC pooled (*continued*)

Variables	(1)	(2)	(3)	(4)
Parental immigration				
Immigrant mother			-0.0205***	-0.0207***
			[0.006]	[0.006]
Immigrant father			0.0088	0.0092
			[0.005]	[0.006]
Cohort (5 year bands)				
Cohort 1		-0.0013		0.0078
		[0.009]		[0.007]
Cohort 2		0.0110		0.0097
		[0.013]		[0.009]
Cohort 3		0.0271**		0.0263**
		[0.013]		[0.012]
Cohort 4		0.0246		0.0321**
		[0.018]		[0.014]
Cohort 5		0.0541***		0.0500***
		[0.021]		[0.016]
Cohort 6		0.0678***		0.0665***
		[0.024]		[0.019]
Cohort 7		0.0648***		0.0639***
		[0.028]		[0.023]
Constant	5.6000***	5.5999***	5.6239***	5.6228***
	[0.005]	[0.005]	[0.006]	[0.006]
Observations	9 366	9 366	9 366	9 366
R-squared	0.248	0.249	0.289	0.292

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.4a. Regression results, Denmark, IALS and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0000	0.0001	-0.0001	0.0000
	[0.004]	[0.004]	[0.004]	[0.004]
Years of schooling	0.0506***	0.0629***	0.0507***	0.0628***
	[0.006]	[0.006]	[0.006]	[0.006]
Years of schooling squared	-0.0009***	-0.0014***	-0.0009***	-0.0014***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0320***	-0.0344***	-0.0312***	-0.0339***
	[0.005]	[0.005]	[0.005]	[0.005]
Age: 45-54	-0.0671***	-0.0955***	-0.0662***	-0.0945***
	[0.006]	[0.007]	[0.006]	[0.007]
Age: 55-64	-0.1225***	-0.1807***	-0.1218***	-0.1795***
	[0.005]	[0.008]	[0.005]	[0.008]
Parental immigration				
Immigrant mother			-0.0247*	-0.0144
			[0.014]	[0.014]
Immigrant father			-0.0244	-0.0148
			[0.024]	[0.023]
Cohort				
Cohort 2		0.0198***		0.0194***
		[0.006]		[0.006]
Cohort 3		0.0559***		0.0550***
		[0.007]		[0.007]
Cohort 4		0.1134***		0.1121***
		[0.010]		[0.010]
Constant	5.1847***	5.0967***	5.1840***	5.0972***
	[0.041]	[0.043]	[0.041]	[0.043]
Observations	6 312	6 312	6 312	6 312
R-squared	0.329	0.348	0.330	0.348

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.4b. Regression results, Finland, IALS and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	0.0015	0.0018	0.0017	0.0021
	[0.004]	[0.004]	[0.004]	[0.004]
Years of schooling	0.0429***	0.0416***	0.0426***	0.0411***
	[0.005]	[0.005]	[0.004]	[0.005]
Years of schooling squared	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0118**	-0.0102*	-0.0111**	-0.0093*
	[0.006]	[0.006]	[0.006]	[0.006]
Age: 45-54	-0.0451***	-0.0304***	-0.0443***	-0.0287***
	[0.006]	[0.007]	[0.006]	[0.007]
Age: 55-64	-0.1050***	-0.0832***	-0.1035***	-0.0801***
	[0.006]	[0.009]	[0.006]	[0.009]
Parental Immigration				
Immigrant mother			-0.0653	-0.0675
			[0.045]	[0.045]
Immigrant father			-0.0924*	-0.0961*
			[0.052]	[0.052]
Cohort				
Cohort 2		-0.0175***		-0.0183***
		[0.006]		[0.006]
Cohort 3		-0.0290***		-0.0307***
		[0.008]		[0.008]
Cohort 4		-0.0289**		-0.0321***
		[0.011]		[0.011]
Constant	5.2727***	5.2883***	5.2746***	5.2920***
	[0.032]	[0.033]	[0.031]	[0.032]
Observations	5 304	5 304	5 304	5 304
R-squared	0.343	0.344	0.346	0.348

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.4c. Regression results, Ireland, IALS and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0109*	-0.0117**	-0.0107*	-0.0116**
	[0.006]	[0.006]	[0.006]	[0.006]
Years of schooling	0.0368***	0.0423***	0.0369***	0.0424***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0755***	-0.0836***	-0.0752***	-0.0837***
	[0.010]	[0.010]	[0.010]	[0.010]
Age: 45-54	-0.1056***	-0.1785***	-0.1053***	-0.1785***
	[0.011]	[0.014]	[0.011]	[0.014]
Age: 55-64	-0.1209***	-0.2371***	-0.1202***	-0.2370***
	[0.011]	[0.018]	[0.011]	[0.018]
Parental immigration				
Immigrant mother			-0.0321	-0.0236
			[0.021]	[0.021]
Immigrant father			0.0090	0.0227
			[0.023]	[0.023]
Cohort				
Cohort 2		0.0772***		0.0773***
		[0.010]		[0.010]
Cohort 3		0.1366***		0.1367***
		[0.015]		[0.015]
Cohort 4		0.1719***		0.1720***
		[0.021]		[0.022]
Constant	5.2395***	5.1560***	5.2386***	5.1551***
	[0.016]	[0.019]	[0.016]	[0.019]
Observations	4 569	4 569	4 569	4 569
R-squared	0.274	0.297	0.274	0.297

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.4d. Regression results, Sweden, IALS and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0109**	-0.0117***	-0.0110**	-0.0118***
	[0.004]	[0.004]	[0.004]	[0.004]
Years of schooling	0.0010	0.0150***	0.0020	0.0152***
	[0.004]	[0.005]	[0.004]	[0.005]
Years of schooling squared	0.0008***	0.0003	0.0008***	0.0003
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0613***	-0.0541***	-0.0585***	-0.0525***
	[0.006]	[0.008]	[0.006]	[0.008]
Age: 45-54	-0.0948***	-0.1237***	-0.0922***	-0.1211***
	[0.006]	[0.007]	[0.006]	[0.007]
Age: 55-64	-0.1607***	-0.1851***	-0.1584***	-0.1818***
	[0.007]	[0.010]	[0.007]	[0.010]
Parental immigration				
Immigrant mother			-0.0290**	-0.0200*
			[0.012]	[0.012]
Immigrant father			-0.0231*	-0.0126
			[0.012]	[0.012]
Cohort				
Cohort 2		0.0270***		0.0257***
		[0.008]		[0.008]
Cohort 3		0.0408***		0.0380***
		[0.008]		[0.008]
Cohort 4		0.1188***		0.1151***
		[0.010]		[0.010]
Constant	5.6312***	5.5207***	5.6251***	5.5205***
	[0.029]	[0.031]	[0.029]	[0.031]
Observations	3 737	3 737	3 737	3 737
R-squared	0.297	0.327	0.301	0.328

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

Table A.4e. Regression results, Belgium, IALS and PIAAC pooled

Variables	(1)	(2)	(3)	(4)
Female	-0.0171***	-0.0170***	-0.0173***	-0.0172***
	[0.005]	[0.005]	[0.005]	[0.005]
Years of schooling	0.0371***	0.0368***	0.0370***	0.0367***
	[0.001]	[0.001]	[0.001]	[0.001]
Years of schooling squared	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	[0.000]	[0.000]	[0.000]	[0.000]
Age of respondent				
Age: 35-44	-0.0329***	-0.0432***	-0.0318***	-0.0423***
	[0.010]	[0.010]	[0.010]	[0.010]
Age: 45-54	-0.0554***	-0.0480***	-0.0546***	-0.0465***
	[0.010]	[0.011]	[0.010]	[0.011]
Age: 55-64	-0.0931***	-0.1037***	-0.0917***	-0.1011***
	[0.011]	[0.014]	[0.011]	[0.015]
Parental immigration				
Immigrant mother			-0.0371**	-0.0388**
			[0.015]	[0.015]
Immigrant father			0.0028	0.0007
			[0.016]	[0.016]
Cohort				
Cohort 2		-0.0213**		-0.0225**
		[0.010]		[0.010]
Cohort 3		-0.0006		-0.0023
		[0.012]		[0.012]
Cohort 4		-0.0365**		-0.0392**
		[0.016]		[0.016]
Constant	5.2553***	5.2719***	5.2558***	5.2735***
	[0.020]	[0.019]	[0.020]	[0.019]
Observations	4 096	4 096	4 096	4 096
R-squared	0.333	0.335	0.334	0.337

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources: OECD (2016); Statistics Canada (2005); Statistics Canada (1995).

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

Juan Francisco Jimeno;[1] Aitor Lacuesta;[2] Marta Martínez-Matute;[2] and Ernesto Villanueva[2]

[1]Banco de España, CEPR and IZA;[2] Banco de España

This paper examines how formal education and experience in the labour market correlate with measures of human capital available in The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The findings are consistent with the notion that, in producing human capital, work experience substitutes formal education at the bottom of the schooling distribution. First, the number of years of working experience correlates with literacy proficiency only among low-educated individuals. Secondly, low-educated workers who only perform simple tasks on their jobs (calculating percentages or reading emails) do better in numeracy and literacy tests than similar employees who did not perform those tasks. Thirdly, workers in jobs intensive in numeric tasks perform relatively better in the numeracy section of the PIAAC test than in the literacy part. Overall, our results suggest that the contribution of on-the-job learning to skill formation is about a third of that of compulsory schooling in most of the countries that participated in PIAAC.

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1. Introduction

Human capital, defined as the cognitive skills that can be acquired in the formal education system and by learning on-the-job, plays a crucial role in shaping labour market outcomes (see Rosen, 1972). Since the seminal study of Mincer (1974) the role of both forms of human capital has been measured using earnings equations that relate the individuals' labour market outcomes to the level of education and work experience. However, it is also well known that earnings at a point in time reflect not only the market value of human capital, but also institutional factors, such as collective bargaining, minimum wages or other factors affecting the reservation wages. Furthermore, wages are observed for employees only, making it difficult to infer the contribution of formal education and on-the-job learning on the human capital acquired by large groups of the population. This is unfortunate, because the effectiveness of active labour market policies focused on job training depends on the relative impact of formal education and work experience in increasing human capital.

The empirical literature has addressed those issues by isolating the causal impact of education and work experience through the use of advanced econometric techniques (instrumental variables, natural experiments)(see Card, 1999, or Murnane et al., 1995). The results from that literature generally confirm that education and work experience increase cognitive skills and labour market outcomes beyond their relationship with other unobserved individual characteristics (Card, 1999; Angrist and Krueger, 1991; Carneiro, Heckman and Vytlacil, 2011).

Our study draws on new data to estimate the contribution of on-the-job training on several measures of cognitive ability of representative samples of the population of eight European countries, focusing on individuals with low levels of formal education.[1,2] By using measures of cognitive abilities available for representative samples of the population we can abstract from several of the econometric issues that arise because wages or labour market outcomes are available for selected samples of the population or affected by institutional factors.

We start by measuring on-the-job learning as the number of years of work experience. Work experience may vary across similar individuals due to extended periods of unemployment or non-participation in the labour market which, in turn, may affect cognitive skills.[3] On the other hand, an active worker engaged in numeric or literacy tasks may also learn skills through learning on-the-job or training activities (see Becker, 1964; Ben Porath, 1967).

The second measure of on-the-job learning takes advantage of the richness of the PIAAC survey that collects information on a wide array of tasks performed on the current or last job. Given that jobs differ in their task content, we analyse whether given the same number of years worked, different intensities in the

1. We assume that there are no differences between unemployed workers who attend training courses and other unemployed or inactive workers. So, when we compare people of the same age and education with different levels of experience, we will be observing the difference in cognitive skills that have been used for more or less time (considering all possible alternatives - informal work, leisure and occupational, vocational or informal studies - equivalent to each other).

2. This paper has been written as support material to the presentation report of the PIAAC study. We thank Luis Miguel Sanz, Francisco Garcia Crespo and Ismael Sanz for their help with the database and, especially, Inge Kukla for her excellent assistance. We also thank Richard Desjardins and participants of the 2nd international PIAAC conference in Haarlem, the Netherlands; for their very useful comments. The opinions and analyses in this study are those of the authors and, therefore, do not necessarily coincide with those of the Bank of Spain or of the Eurosystem.

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).

numeric or literacy tasks (basic or advanced) performed in the last or current job contribute to better numeracy or literacy scores.

However, the extent to which work experience can increase the cognitive skills of a person depends on unobserved factors like pre-labour market cognitive or even non-cognitive skills.[4] Our analysis takes into account a significant number of factors that approximate individual differences but cannot control for all sources of unobserved differences. For that reason, we implement a worker-level fixed-effect strategy that draws on the availability of multiple measures of cognitive skills for the same individual. That specification allows us to relate the relative intensity of numeracy versus literacy tasks in her job to the relative score in numeracy versus literacy tests, thus absorbing any individual level characteristic that is constant across human capital measures.

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

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

The rest of the paper is organised as follows. Section 2 describes the test. Section 3 describes the data. Section 4 discusses the link between working experience and numeracy scores, while sections 5 and 6 discuss and quantify the link between tasks on-the-job and numeracy and literacy scores. Section 7 presents the main conclusions.

2. The test

We assume that human capital C is acquired either through formal education S or by performing tasks on-the-job work experience–denoted by J. Individuals may also vary in their initial endowment of human capital C_0 –a measure that summarises factors related to innate ability.

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

The tasks performed on-the-job and formal schooling S may affect the stock of acquired skills C in a non-linear fashion. On one hand, the tasks learnt on-the-job could complement formal education if highly skilled individuals learned the most from performing sophisticated tasks on their job –in which case α_3

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

would be positive. Alternatively, one could think that on-the-job learning is a substitute for formal education if a certain set of skills –like using a calculator- can be learnt either at school or through practice on-the-job. In that case, α_3 could be negative.

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

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

In our case, the subscript *m* can take two values, depending on the exact measure of skills we use: literacy (*l*) or numeracy (*n*). In what follows, we use two different measures of learning on-the-job J_m. The first measure is the *number of years worked full time*, an indicator of exposure to on-the-job learning. The second measure of J_m denotes the skill content of the current or last job, and reflects whether or not an individual performs *particular tasks on-the-job* - in our case, can be either numeracy or literacy-related. Finally, we assume that ε_m is an unobserved factor uncorrelated with both tasks and the initial amount of human capital, but that may reflect an initial ability for maths vs. literacy.

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

The parameter of interest. In this study, we mainly focus on α_2 the impact of tasks on the job on overall measures of skills C. Several reasons lead us to expect that α_2 varies across individuals. We already mentioned that α_2 may vary across groups with different levels of formal schooling depending on whether on-the-job learning is a complement or a substitute for formal schooling. As we mention below, sorting of individuals across jobs or mismatch can also make that the impact of tasks on human capital is heterogeneous across individuals.

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

We address the omitted variable bias caused by the fact that C_0 is not observable by relying on two measures of human capital C_m, *m=n,l*. Assume that performing numerical tasks on the job has an impact on numeric ability, and that performing literacy tasks on the job has a similar impact on reading ability. In that case, one can see if workers who specialise in jobs with a relatively higher numeracy content –relative to the literacy one- end up with a relatively higher numeracy score –relative to the score in the literacy test. In other words, under the assumptions that $\alpha_{2,n} = \alpha_{2,l}$ and that $\alpha_{3,n} = \alpha_{3,l}$ one can take the difference between human capital related to numeracy and that related to literacy:

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

Model (3) identifies the impact of tasks performed on-the-job on particular forms of human capital by comparing individuals who have different degrees of specialisation on their jobs. The advantage of Model (3) over Model (2) is that it implicitly holds constant an unobserved individual fixed-effect that reflects generic initial human capital acquired before entering the labour market.

Potential sources of biases

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

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

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

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

Indeed, as Table 2 suggests, a non-negligible fraction of college workers in the countries we consider conduct basic numeracy or literacy tasks on their jobs. It is not clear how mismatch affects our estimates. Firstly, our focus lies on workers with basic schooling, who are unlikely to be in jobs requiring skills below their abilities. In addition, if mismatched workers work in jobs with a similarly poor content of numeracy and reading tasks, once we take differences in numeric vs literacy task intensity in Model (3), we implicitly control for the degree of mismatch.[5] Finally, we note that it is very likely that there is substantial dispersion in the skill content of jobs and in the workers' ability to acquire skills from exposure to those tasks. In other words, α_2 is very likely to be heterogeneous across workers. At this stage, we can only aim to recover the average effect of on-the-job learning on skills, leaving an analysis of heterogeneous impacts to a future version of the study.

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

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

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

In that case OLS estimates of α_2 would be upwardly biased, as they attribute to on-the-job learning what really is the result of workers sorting across jobs. In other words, even if doing specific tasks on-the-job did not increase skills at all, an OLS estimate of α_2 could be positive simply because individuals with an initial (pre-market) comparative advantage in maths end up in more maths-intensive jobs.

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

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

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

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

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

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

Testable hypotheses

In sum, we test three main hypotheses:

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

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

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

3. Database

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

In each country a representative sample of adults 16-65 years old took a direct assessment of their proficiency in literacy and numeracy. The survey was implemented either by computer or with paper and pencil.[6] The assessment also tested proficiency in problem solving in technology-rich environments, but we only use literacy and numeracy, as the former was not administered in all countries.[7,8]

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

Experience. In particular, work experience is constructed with the individuals' responses to the question: “In total, approximately how many years have you been in paid work? Include only those years in which you worked for six months or more, full time or part time”.

Tasks. The survey asks each employed respondent about how many times he or she conducted a particular task during the last month. The survey asked non-employed respondents about the tasks done in their last job. The number of tasks listed in the survey is large, and we have classified them as either numeracy- or literacy-related. Numeracy-related tasks include elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams, elaborating graphs or using algebra. Literacy-related tasks are reading email, reading guides, reading manuals, writing emails, writing reports, reading articles, reading academic journals, reading books and writing articles.

Formal education. We group individuals in three schooling levels. The first is primary education or less. The second is composed of individuals having completed either baccalaureate studies or forms of Vocational Training that, according to the ISCED classification, do not constitute university education. The third group is composed of individuals with any type of university education, including those forms of Vocational that ISCED considers equivalent to college.

6. Individuals who answered with paper exams have been controlled with a dummy in the regressions.

7. Details about the definition of each domain are given by OECD (2013).

8. In this version of the paper, we use only one of the ten different imputations of the score for each test for each individual, so that the results are preliminary. Each score is measured on a 500-point scale and, for tables 1-4, we have not standardised the scores.

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 65 years of age. However, in several instances, we restrict the sample to respondents below 45 years of age as the link between experience and skills weakens considerably after that age. In addition, as we compare in many instances the relationship between work experience or tasks and performance at the tests across schooling groups, we cut the sample below 26 to avoid measuring experience at years when college graduates are unlikely to work. The 25-year age limit also avoids the problems associated with greater practice in exam preparation among college students.

Summary statistics: Experience and tasks

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

Table 1. Summary statistics

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

Notes:

Population 26-45 years old.

a. Full sample includes respondents from Spain, Italy, the United Kingdom (England and Northern Ireland), Ireland, Norway, Sweden, Estonia and the Netherlands.

b. The standard deviation of the numeracy score is 52.18 (full sample) and that of the literacy score is 47.43. Both measures are for the full sample.

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table 2 shows to what extent workers perform different tasks on their job. As discussed in section 2, we distinguish between simple and advanced tasks, as their impact on human capital accumulation is likely to vary across educational groups. Regarding numerical tasks, we used Principal Component Analysis to classify tasks into advanced and simple, and identified elaborating a budget, using a calculator, reading bills, using fractions or percentages and reading diagrams as simple tasks. Conversely, we classify elaborating graphs or using algebra as advanced tasks.[9] Similarly, we classified reading email, reading guides, reading manuals, writing emails, writing reports and reading articles as simple literacy tasks, while reading academic journals, reading books and writing articles were classified as advanced literacy tasks.

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

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

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

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

Level of education	Full sample	Spain	Italy	United Kingdom	Ireland	Norway	Sweden	Estonia	Netherlands
				Basic numeracy tasks					
Basic	30.84	31.30	35.50	28.13	22.82	36.69	32.26	30.08	29.91
Bachelor	32.40	33.40	34.62	32.36	33.10	33.63	36.77	25.29	29.99
College	19.39	19.94	22.73	18.88	21.36	18.25	21.97	13.56	18.44
				Advanced numeracy tasks					
Basic	19.34	13.43	8.14	16.37	11.63	28.63	23.39	28.46	24.63
Bachelor	41.50	33.21	32.25	37.69	28.19	50.07	45.68	53.50	51.39
College	68.68	61.40	57.27	68.97	62.60	75.00	72.17	77.55	74.45
Obs.	19738	2617	2065	3862	2921	1925	1593	2925	1830

Level of education	Full sample	Spain	Italy	United Kingdom	Ireland	Norway	Sweden	Estonia	Netherlands
				Basic literacy tasks					
Basic	29.61	30.19	27.2	29.03	27.07	22.58	24.19	38.21	38.42
Bachelor	27.30	37.02	29.77	28.12	32.02	14.05	19.36	32.29	25.76
College	11.29	20.24	12.95	13.5	15.23	4.56	6.79	8.73	8.33
				Advanced literacy tasks					
Basic	29.45	18.89	17.75	23.53	17.23	56.45	38.71	28.73	34.31
Bachelor	54.44	36.64	44.81	50.11	37.73	79.07	70.61	51.53	64.99
College	81.63	66.54	76.59	78.02	74.28	92.76	90.81	85.5	88.52
Obs.	19738	2617	2065	3862	2921	1925	1593	2925	1830

Notes:

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

b. Each entry is the percentage of respondent reporting having performed at least one task during the last month in their current or last job. Tasks are grouped depending on the level of:

- Basic numeracy tasks are: prepare budgets, use calculator, read bills, use fractions and read diagrams.
- Advanced numeracy tasks are: create graphs and use algebra.
- Basic literacy tasks are: read guides, read emails, read handbooks, write emails, write reports and read papers.
- Advanced literacy tasks are: read academic journals, read books and write papers.

c. The full sample includes Spain, Italy, the United Kingdom (England and Northern Ireland), Ireland, Norway, Sweden, Estonia and the Netherlands.

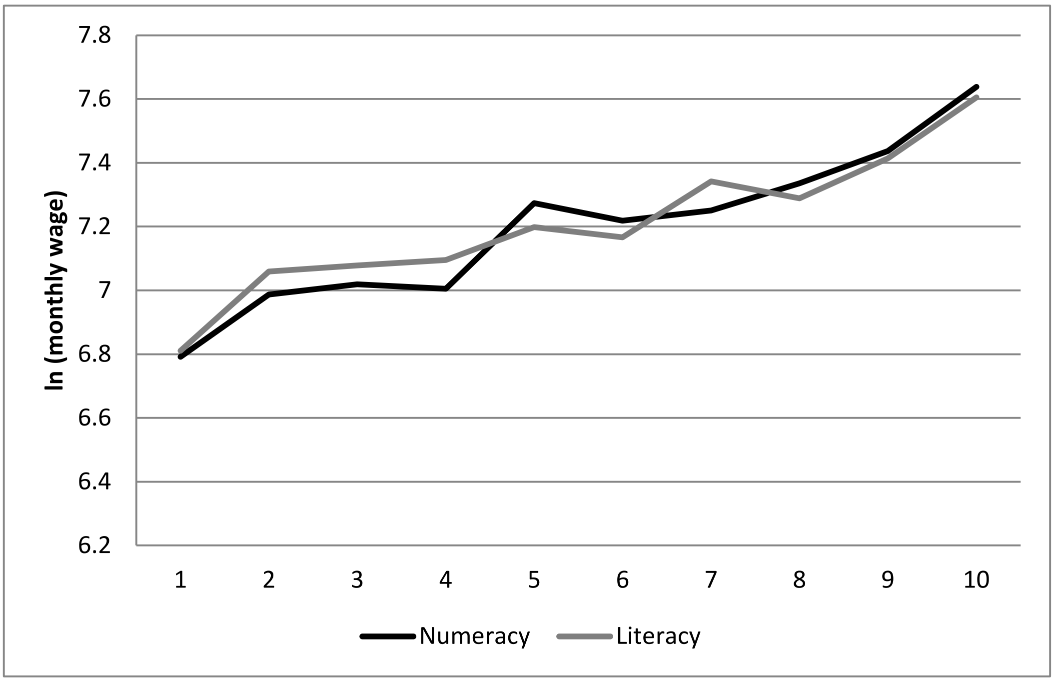
Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The importance of cognitive skills

Before investigating why labour market experience might positively impact cognitive skills, it is worth analysing the degree of association between declared wages and cognitive skills, as measured by the tests in the PIAAC sample. Only to the extent that both variables are correlated some conclusions about the importance of cognitive skills for job performance can be drawn. Figure 1 relates the results of numeracy and literacy tests to wage earnings in each decile of the distribution of the numeracy proficiency in Spain. The statistical association is particularly pronounced at the higher deciles of the wage distribution, suggesting that cognitive skills measured by the tests are relevant to job performance in all deciles of the distribution –see Hanushek et al., 2015 for similar evidence. The finding of a strong correlation between performance in PIAAC and wages at the top of the wage distribution is consistent with the idea that cognitive skills are rewarded in the labour market, especially at the top of the wage distribution.

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

Figure 1. Wage earnings and cognitive skills



Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

4. Work experience and cognitive skills

Table 3a tests Model (2) by running country-specific regressions of the numeracy score in PIAAC on a flexible function of years of working experience, interacted with schooling dummies. To attain more precision, we only interact with schooling the main effect of experience, assuming that the squared term in experience is common across schooling groups (a strong assumption we relax below). In addition to years of experience and education, we also include demographic and attitudinal variables as controls.[10] To allow the effect of experience on test scores to vary over the life span, experience is included as a second-order polynomial.

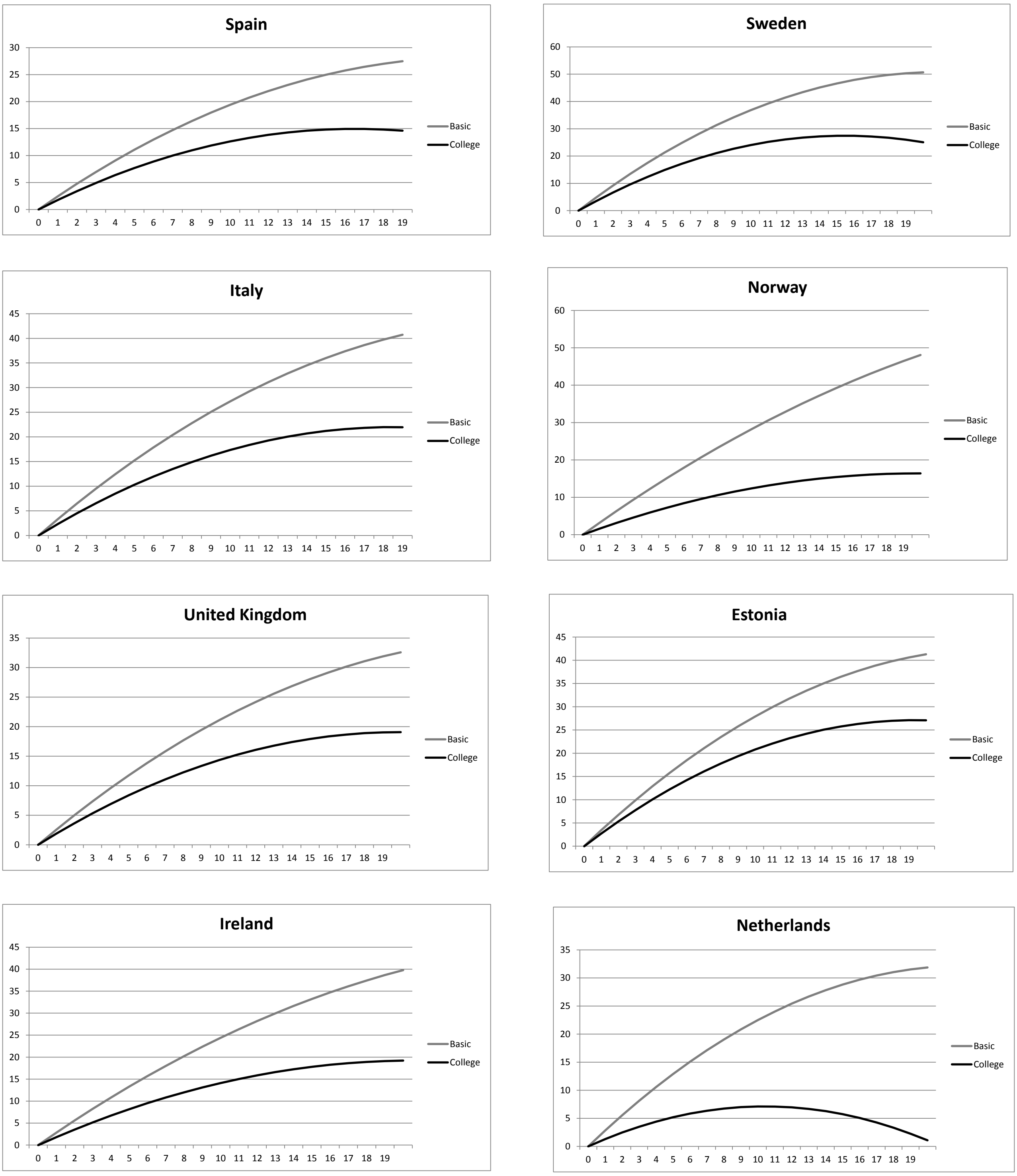
Regardless the country of residence and among respondents with basic schooling, ten years of labour market experience are associated with an increase in the score in the numeracy test. For example, a Spanish worker with basic schooling and 15 years of experience scores 8.4 (=.84*10) additional points in the numeracy test than a similarly schooled worker with 5 years of working experience. The same increase of 10 years results in an increase of 19.8 points in the numeracy score in Norway (the standard deviation of the marginal distribution of the scores is about 50 points). While cross-country estimates are hard to compare because of the variation in the standard deviation of the scores across countries, the finding that experience is positively associated with the numeracy score of respondents with basic schooling holds in all countries considered.

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

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

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

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



Notes: a. Each figure shows for each country how the predicted numeracy score varies with working experience, for an individual with a college degree (black line) and another with basic schooling (grey line). The prediction is for a single male aged between 40 and 45 years of age, with fair health and no interest in learning new things. The prediction is obtained using the estimated coefficients shown in Table 3b. To permit comparisons along the life cycle, the numerical score for 0 years of experience is normalised to zero for each schooling group. c. Numeracy scores are not adjusted for the country-specific standard deviation.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table 3b relaxes the strong functional form assumptions implicit in Table 3a. There, we conduct local linear regressions of the numeracy score on the number of years of experience separately for each education-country cell. The advantage of that specification is that we can capture more accurately the concavity of the effect of experience on numerical test scores while at the same time we hold the covariates in footnote 14 constant.[11] The flexibility of the models estimated in Table 3b comes at the cost that some cells have too few observations to conduct the analysis (cases of the Netherlands and Sweden). The results in Tables 3b and 3a are qualitatively similar: in all countries but in Estonia the link between experience and the numeracy score is strongest for individuals with basic schooling at low levels of working experience. The effect of one extra year of experience is still noticeable after 15 years in four out of the six countries where we could estimate the regression (the exceptions being Italy and Estonia). The link between years of working experience and average numeracy scores among respondents with a college degree is statistically significant at the beginning of the career only in England/Northern Ireland and in Norway. After 5 or 10 years is basically zero in all countries considered.

11. Namely, we pose a flexible relationship between numeracy scores and experience, while controlling for a linear index of the covariates at the bottom of Table 3a. We then fit local linear regressions of numeracy scores and each of the covariates in the index on experience and take the residuals from those regressions. We make a linear regression of those residuals to partial out the impact of the linear index of covariates. Finally, we fit local linear regressions of numeracy score minus the estimated local index on experience. See Robinson (1988).

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

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

Notes:

Respondents in Spain, Italy, Ireland, the United Kingdom (England and Northern Ireland), Sweden, Norway, Estonia and the Netherlands.

a. The sample contains respondents 26 to 45 years old. The dependent variable is the numeracy score (measured from 0 to 500). All models include as regressors (not shown) a dummy for female, two dummies with the education level of the respondent (omitted value: basic schooling), a dummy that takes value one if respondent is not working, two dummies with the level of education of the mother (bachelor and college), a dummy that takes value 1 if foreign born, another for married, 4 dummies with 5-year age bands, a dummy for exam done on paper, one dummy for poor health, another for "enjoy learning new things", and a final one for no work experience.

b. Experience is the deviation of the number of years worked full time minus 15. The specification in Table 3a assumes that the estimate of (experience-15) squared is common across all education groups. The assumption is relaxed in Table 3b. The estimates shown are the coefficients of experience, where the omitted group is basic schooling.

Heteroscedasticity-adjusted standard errors in parentheses.

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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

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

Notes:

Respondents in Spain, Italy, Ireland, the United Kingdom (England and Northern Ireland) Sweden, Norway, Estonia and the Netherlands.

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

b. The coefficients shown are the impact of an additional year of experience on the numeracy score, estimated for different years of experience. The semiparametric analysis is estimated using local polynomial regressors for each year of experience using a common bandwidth of 0.8 years. The covariates listed in Table 3a are included linearly and then partialed out as in Robinson (1988).

The standard errors are bootstrapped 50 times.

c. n.a. on a cell means that the subsample was too small to conduct a semiparametric estimation.

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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

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

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

5. Job tasks and cognitive skills

We now test our second hypothesis: simple tasks correlate with numeracy and literacy scores for workers with basic schooling. We regress the numeracy and literacy test scores on indicators of the type of tasks performed on-the-job, all interacted with dummies of school attainment. In particular, the indicator "basic numeric tasks" ("advanced numeric tasks") takes value 1 if the worker reports having performed *any* of the basic numeric (advanced) tasks listed in the data section during the last month, and zero otherwise. As in previous specifications, the country-specific regressions shown in Table 4 hold constant the number of years of experience and the socio-economic factors described at the bottom of Table 3a.

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

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

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

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

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

Notes:

a. Sample contains respondents aged 26 to 45 years old.

b. The dependent variable is the score in the numeracy test, measured from 0 to 500 -it is not normalised. The estimated method is OLS. Additional regressors (not shown) are: working experience minus 12, and its interaction with dummies of bachelor and college as well as all the covariates listed in Table 3a: foreigner, couple, does not work, age (grouped into 5 years), do the exam in paper, health, enjoy learning new things, women, no working experience.

c. The dummy "Basic tasks Num" takes value 1 if the respondent reports having performed at least one numerical task at least once a month in his or her current or last job and zero otherwise.

The "basic numeracy tasks" include elaborating a budget, using a calculator, reading bills, using fractions or reading diagrams. The "advanced numeracy tasks" include having generated graphs or using algebra.

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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

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

Notes:

a. Sample contains respondents aged 26 to 45 years old.

b. The dependent variable is the score in the literacy test, measured from 0 to 500 - it is not normalised. The estimated method is OLS. Additional regressors (not shown) are: working experience minus 12, and its interaction with dummies of bachelor and college as well as all the covariates listed in Table 3a: foreigner, couple, does not work, age (grouped into 5 years), do the exam in paper, health, enjoy learning new things, women, no working experience.

c. The dummy "Basic tasksLit" (Advanced tasksLit) takes value 1 if the respondent reports having performed at least one basic (advanced) task at least once a month in his or her current or last job and zero otherwise.

"Basic literacy tasks" include reading email, reading guides, reading manuals, writing emails, writing reports, reading articles. "Advanced literacy tasks" include reading academic journals, reading books and writing articles.

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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

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

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

6. Identifying a causal relationship

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

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

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

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

An illustration: Task specialisation by occupation and industry

We illustrate the different degrees of numeracy specialisation by aggregating skills at the occupation and industry level. Table A.2 in Annex A shows the different task intensity of industries that employ low-educated individuals and Table A.3 in Annex A shows the different tasks intensity of occupations of the same sample. We focus on occupations (Table A.3). Numeracy and literacy tasks have been summarised separately by Principal Component Analysis and the first component has been normalised to the interval (0,1) in order to provide a ranking of the task content of the occupation. Examples of the main tasks conducted on-the-job are also provided in Tables A.2 and A.3 –note that all tasks are normalised by the task-specific mean, so a number above one implies that workers in the occupation conduct the particular task more often than the average.

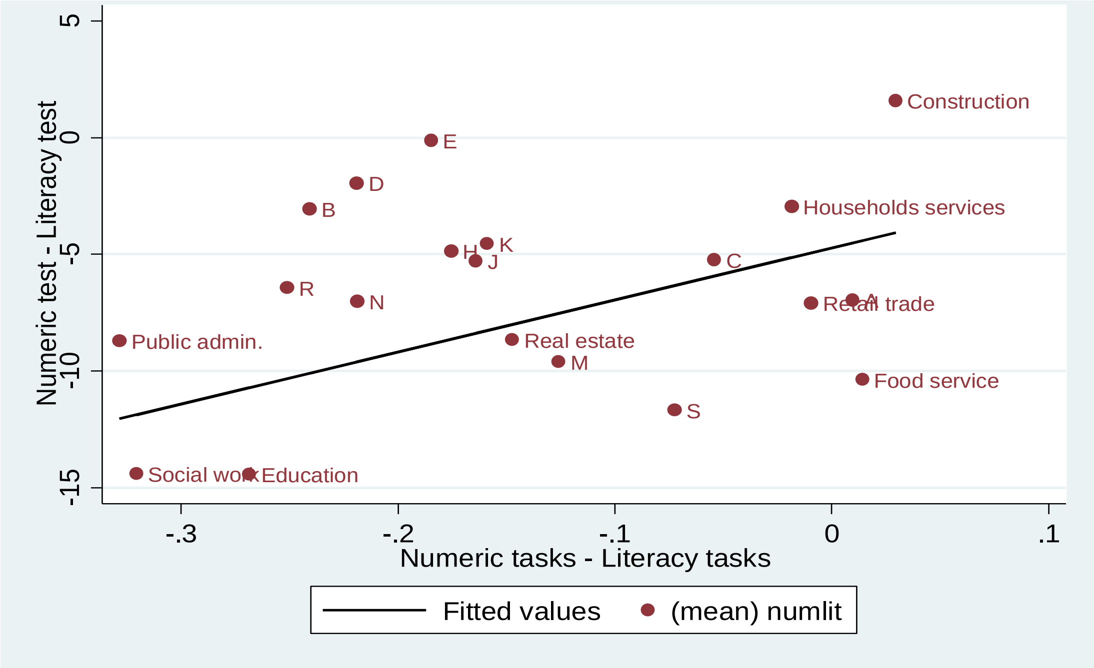
To fix ideas, we examine two polar cases. The first are *personal care workers* (occupation number 53), who constitute 9.8 % of all individuals with basic schooling in the full sample. Workers in that occupation rank relatively high in literacy tasks (0.20) but less so in the numerical task ranking (.05, Table A.3, second column). The tasks conducted by the average person in the occupation give clues about the rationale for those rankings. Personal care workers elaborate budgets, read diagrams or use calculators with an intensity that falls well below the mean (i.e. the corresponding entry under each of those tasks is well below 1). Conversely, personal care workers read guides or emails more frequently than the average worker does. In that sense, personal care workers are specialised in literacy tasks.

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

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

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

Figure 3a. Differential numeracy-literacy score versus differential tasks by industry (low-educated)



Notes:

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

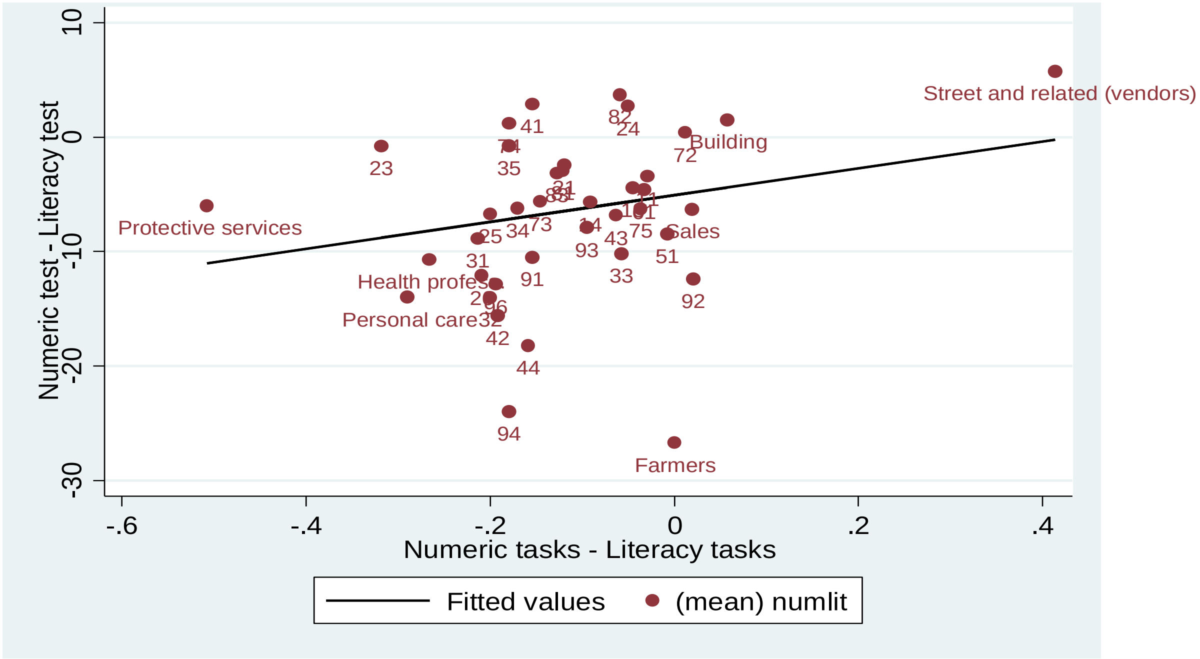
b. The industry codes used in this figure can be found in Table A.2 in Annex A.

c. Only representative countries are considered (Spain, Italy, Ireland, the United Kingdom, Sweden, Norway, Estonia and the Netherlands).

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 3b. Differential numeracy-literacy score versus differential tasks by occupation (basic schooling)



Notes:

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

b. The occupational codes used in this figure can be found in Table A.3 in Annex A.

c. Only representative countries are considered (Spain, Italy, Ireland, the United Kingdom, Sweden, Norway, Estonia and the Netherlands).

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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

Regression analysis

Table 5a implements a version of Model (3) on the full sample of countries.[12] We pool observation of all countries and introduce country-specific dummies. The numeracy and literacy scores are normalised by the country-specific standard deviation. The first set of regressions use the full sample of workers (between 16 and 65 years of age) and do not distinguish between simple and advanced tasks.

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

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

Overall, the results in Table 5a are again consistent with the notion that conducting tasks on the job increases skills of workers, and that such effect is strongest for workers with basic schooling. The result points again at formal schooling and practice on the job being substitutes – a surprising finding, as one could well expect that the performance of tasks on the job reinforces pre-labour market differences associated to differences in formal schooling.

Table 5a. The impact of task specialisation on relative performance in numeracy and literacy score (all countries pooled)

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

Notes:

Respondents in Spain, Italy, Ireland, the United Kingdom (England and Northern Ireland), Sweden, Norway, Estonia and the Netherlands).

a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test, each normalised by its standard deviation. The independent variable is the individual-specific difference between the frequency of numeracy and literacy tasks performed in the job. Numeric task is the fraction of numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of literacy tasks reported. The difference between "numeric" and "literacy task" is the degree of specialisation in one type of tasks. It takes value 1 if the individual performs *all* numeric tasks in his or her job and *none* of the literacy ones.

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

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table 5b. The impact of task specialisation on relative performance in numeracy and literacy score (all countries pooled)

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

Notes:

Respondents in Spain, Italy, Ireland, the United Kingdom (England and Northern Ireland), Sweden, Norway, Estonia, the Netherlands, the Czech Republic, France, Finland, Korea, the Russian Federation and the Slovak Republic).

a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test, each normalised by its standard deviation. The independent variable is the difference between two variables: numeracy tasks and literacy tasks. It takes value 1 if the individual reported having performed all tasks. Numeric task is the fraction of numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of literacy tasks reported. The difference between "numeric" and "literacy task" is the degree of specialisation in one type of tasks. It takes value 1 if the individual performs *all* numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5-year bands). In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

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

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Heterogeneity by age groups. As mentioned above, there may be substantial heterogeneity in the link between tasks conducted on the job and the acquisition of human capital. Green and Riddell (2013) document a cohort-level fall in literacy after age 45, suggesting that skills deteriorate over the life-cycle. Hence, we split the sample below and above 45 years of age. Remarkably, the estimated link between specialisation in numeracy tasks and human capital is very similar in the full sample and in the below-45 sample: full specialisation in numeracy tasks increases the relative numeracy score by 22% of one standard deviation in the full 16-65 sample and by 23% of one standard deviation in the 25-45 sample. The only noticeable difference across specifications is that the impact of full specialisation in numeracy tasks on relative numeracy scores is slightly lower in the prime age sample of college graduates: 17% (=.225-.0547) of one standard deviation in the full sample vs 15%=(.229-.0784) of one standard deviation in the prime age sample.[13]

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

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

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

13. Those results suggest that the possible skill deterioration documented in previous could be explained by differences in the type of tasks conducted in job over the life cycle, an area we plan to examine in closer detail.

Table 6a. The impact of task specialisation on relative performance in numeracy and literacy score (all countries pooled)

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

Notes:

a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test, each normalised by its standard deviation. The independent variable is the difference between two variables: numeracy basic tasks and literacy basic tasks. It takes value 1 if the individual reported having performed all basic tasks. Numeric task is the fraction of basic numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of basic literacy tasks reported. The difference between "numeric" and "literacy task" is the degree of specialisation in one type of tasks. It takes value 1 if the individual performs *all* basic numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5-year bands). In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table 6b. The impact of task specialisation on relative performance in numeracy and literacy score (all countries pooled)

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

Notes:

a. The dependent variable is the individual-specific difference between the score in the numeracy test and the score in the literacy test, each normalised by standard deviation. The independent variable is the difference between two variables: numeracy basic tasks and literacy basic tasks. It takes value 1 if the individual reported having performed all basic tasks. Numeric task is the fraction of basic numerical tasks that the respondents reports having performed in his or her job (current or last). Literacy task is the fraction of basic literacy tasks reported. The difference between "numeric" and "literacy task" is the degree of specialisation in one type of tasks. It takes value 1 if the individual performs *all* basic numeric tasks in his or her job and *none* of the literacy ones.

b. The additional regressors (not shown) are: a quadratic polynomial of the number of years of working experience, two indicators of the educational level of the respondent (high school and college), the interaction between education and years of working experience, and age dummies (grouped in 5-year bands). In addition, we include intercepts for female, foreign born, whether the respondent lives with his or her couple, whether he or she does not work, whether the exam was done in paper, two dummies with self-assessed health status and two intercepts denoting if the respondent enjoys learning new things.

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

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Overall, we draw three conclusions from Table 6a:

1. Low-educated workers who fully specialise in simple numeracy tasks obtain higher numeracy scores compared to those who do not specialise. The magnitude of the impact is about 12% of one standard deviation, and is present in basically all sample.

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

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

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

Adjusting estimates for sorting across jobs. The finding that specialisation in basic numeracy tasks results in a weaker relative performance in the numeracy test among workers with either a high school or a college degree than within the group of respondents with basic schooling is consistent with our conjecture in section 2. There, we assume that workers with a high school or college degree cannot increase their numeracy skills by performing simple tasks on-the-job, as those skills should be acquired in the formal school system.

Under the previous assumption, the 4.34% of one standard deviation differential increase in the numeracy score when a worker with a high school diploma specialises in basic numeracy tasks degree mainly picks up a selection effect.[14] Subtracting the sorting effect (4.34) from the 11.8 estimate in the first column yields 7.4% of one standard deviation as the impact of full specialisation on numeracy scores, once one takes into account selection effects.

Assessing the magnitude of the estimates

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

Our estimates suggest that specialising in numeracy tasks increases the differential numerical score of individuals with basic education by about 12% of one standard deviation (Table 6a, row 1 column 1). If we further assume that there are selection effects that can be identified by the impact of specialisation on numeracy scores among high-school graduates, the corresponding estimate would be 7.44% of one standard deviation. The 7.44 estimate is the 11.8% of one standard deviation return of basic school workers - first row first column of Table 6a - net of our estimate of the selection effect. In turn, the selection effect

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

is the impact of specialisation in numeracy tasks on numeracy scores for high-school workers (4.34% of one standard deviation obtained in turn by adding up the first and second rows of Table 6a, column 1).

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

Hanushek et al. (2015) estimate that increasing compulsory education by one year increases skills by between 2.7% and 2.9% of one standard deviation in the United States. Hence, one extra year of schooling would be equivalent to between 1.5=(2.7/1.8) and 4.3 years (=2.9/.67) of on-the-job learning.

7. Conclusions

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

We also dig into the possible channels behind these results. In particular we examine if the type of tasks performed at work explain the effect of labour market experience on the accumulation of cognitive skills. Indeed, we find that, indeed, the type of tasks performed at work matter. Among workers with primary education numeracy scores are in most countries between 6 and 15 raw points (or between 11 and 29.6% of one standard deviation) higher among individuals who perform basic numeracy tasks at work – such as using a calculator, calculating percentage or reading graphs. These basic numeracy tasks contribute little to the scores in numeracy or literacy tests of respondents with a high school or college degree. By contrast, the results in the tests are higher among the group of qualified individuals who perform advanced tasks. When we control for individual fixed effects by analysing how the relative performance in numeracy versus literacy varies with the differential exposure to numeracy versus literacy tasks on-the-job, we find that full specialisation in basic numerical tasks increases the relative numeracy score by between 7.4% and 11.8% of one standard deviation. Our results are consistent with the notion that formal schooling and on-the-job learning are substitute inputs in human capital production for workers with low levels of education.

We still view our results as preliminary. If confirmed, our findings have some implications for the design of active labour market policies. Firstly, cognitive test scores could be a good predictor of human capital that could indeed be easily checked for all unemployed. Secondly, specific tasks on-the-job might contribute to increase cognitive skills for low-educated individuals. While the tentative rate of return to on-the-job training that we have estimated is about a third of that of formal schooling, the costs of increasing school attendance for prime aged workers may be substantial. Thirdly, the amount of on-the-job learning is determined by jobs requirements, which vary greatly across sectors.

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ANNEX A. APPENDIX TABLES

Table A.1. Percentages of workers performing numeracy and literacy tasks

Level of education	Spain	Italy	United Kingdom	Ireland	Norway	Sweden	Estonia	Netherlands
				Basic numeracy tasks				
Basic	15.56	13.36	16.75	15.21	26.61	18.55	13.82	15.25
Bachelor	24.43	23.94	24.4	24.26	29.9	32.73	21.29	25.76
College	18.95	21.82	25.48	23.8	23.61	29.16	16.99	19.13
				Advanced numeracy tasks				
Basic	4.44	3	5.88	2.91	12.5	10	6.78	10.56
Bachelor	16	17.61	18.99	13.56	28.1	24.09	26.71	26.16
College	39.39	37.05	44.42	38.36	51.29	50.07	58.61	56.01
Obs.	2 617	2 065	3 862	2 921	1 925	1 593	2 925	1 830

Table A.1. Percentages of workers performing numeracy and literacy tasks (*continued*)

Level of education	Spain	Italy	United Kingdom	Ireland	Norway	Sweden	Estonia	Netherlands
				Basic literacy asks				
Basic	0.74	1	2.43	1.57	3.63	4	0.27	5.57
Bachelor	3.24	5.54	6.87	3.84	7.92	10.03	6.28	10.96
College	11.94	17.05	27.7	16.85	20.63	25.03	25.18	36.61
				Advanced literacy tasks				
Basic	0	0	0	0	0	0	0	0
Bachelor	0	0	0	0	0	0	0	0
College	0	0	0	0	0	0	0	0
Obs.	2 617	2 065	3 862	2 921	1 925	1 593	2 925	1 830

Notes:

a. Sample is composed of people of 26 to 45 years old (PIAAC database).

b. Numbers of the tables mean the percentage of people doing all tasks of the same group during the last month. Tasks are grouped depending on the level of difficulty and the type of subject. Basic numeracy tasks: elaborating a budget, using a calculator, reading bills, using fractions or percentages, reading diagrams. Advanced numeracy tasks: elaborating graphs or using algebra. Basic literacy tasks: reading email, reading guides, reading manuals, writing emails, writing reports, reading articles. Advanced literacy tasks: reading academic journals, reading books and writing articles.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.2. Frequency of numeracy and literacy tasks by industry – workers with basic schooling

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

Notes:

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A.3. Frequency of numeracy and literacy tasks by occupation – workers with basic schooling

Occupation (ISCO classification)	Share of workers (basic schooling)	PCA numeracy	PCA literacy	Basic numeracy tasks				Basic literacy		
				Elaborate budgets	Use calculator	Use fractions	Read diagrams	Read emails	Read guides	Write emails
		(scaled 0-1)		(Relative to the average)				(Relative to the average)		
11 Chief executives, senior officials and legislators	0.440	0.276	0.287	0.000	1.740	2.104	0.863	0.000	1.493	0.000
12 Administrative and commercial managers	0.720	0.442	0.422	2.291	0.000	2.057	1.845	2.050	1.551	1.940
13 Production and specialised services managers	1.401	0.317	0.338	2.149	1.696	1.785	1.491	1.985	1.360	1.760
14 Hospitality, retail and other services managers	1.881	0.339	0.316	1.910	1.711	1.576	0.656	1.940	1.432	1.529
21 Science and engineering professionals	0.200	0.349	0.339	1.456	1.149	1.851	1.898	0.000	0.000	1.643
22 Health professionals	0.200	0.133	0.347	1.941	0.766	0.926	1.423	0.000	1.313	0.000
23 Teaching professionals	0.360	0.108	0.228	0.809	0.638	0.771	0.791	1.447	1.095	1.141
24 Business and administration professionals	0.480	0.386	0.417	1.819	1.595	1.736	1.779	1.809	0.000	1.882
25 Information and communications technology professionals	0.400	0.384	0.507	1.941	0.000	1.620	2.135	0.000	1.478	1.848
26 Legal, social and cultural professionals	0.360	0.169	0.401	1.348	1.064	1.286	1.318	1.930	1.277	1.825
31 Science and engineering associate professionals	1.561	0.243	0.326	0.871	1.522	1.306	1.703	1.781	1.473	1.632
32 Health associate professionals	0.800	0.178	0.256	0.849	1.053	1.157	1.067	1.303	1.478	1.027
33 Business and administration associate professionals	2.641	0.348	0.380	1.875	1.740	1.683	1.474	2.007	1.368	1.836
34 Legal, social, cultural and related associate professionals	1.361	0.193	0.255	1.356	0.901	1.021	0.767	1.341	1.207	1.148
35 Information and communications technicians	0.240	0.235	0.392	1.617	1.595	1.543	1.581	0.000	1.095	0.000
41 General and keyboard clerks	0.080	0.206	0.262	1.248	1.367	0.727	0.746	2.109	1.173	1.819
42 Customer services clerks	1.401	0.268	0.337	1.266	1.373	1.207	0.825	1.935	1.392	1.607
43 Numerical and material recording clerks	1.841	0.236	0.227	1.115	1.320	1.250	0.791	1.397	1.170	1.275
44 Other clerical support workers	3.481	0.249	0.309	1.115	1.552	1.188	0.962	1.819	1.376	1.665
51 Personal service workers	1.481	0.133	0.136	1.213	0.947	0.649	0.290	0.875	0.896	0.660
52 Sales workers	7.843	0.204	0.171	1.574	1.344	0.954	0.542	1.249	1.146	0.813
53 Personal care workers	9.804	0.054	0.197	0.416	0.580	0.410	0.474	1.303	1.051	0.986

Table A.3. Frequency of numeracy and literacy tasks by occupation – workers with basic schooling (*continued*)

Occupation (ISCO classification)	Share of workers (basic schooling)	PCA numeracy	PCA literacy	Basic numeracy tasks				Basic literacy		
				Elaborate budgets	Use calculator	Use fractions	Read diagrams	Read emails	Read guides	Write emails
		(scaled 0-1)		(Relative to the average)				(Relative to the average)		
54 Protective services workers	7.003	0.085	0.301	0.527	0.624	0.252	0.980	1.510	1.463	1.384
61 Market-oriented skilled agricultural workers	1.841	0.116	0.141	1.431	1.031	0.860	0.669	1.169	1.074	1.027
62 Market-oriented skilled forestry, fishery and hunting workers	3.121	0.140	0.128	0.809	0.893	0.926	0.791	0.579	0.438	0.685
63 Subsistence farmers, fishers, hunters and gatherers	0.600	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
71 Building and related trades workers, excluding electricians	0.040	0.153	0.118	1.028	1.062	0.990	1.202	0.863	1.104	0.610
72 Metal, machinery and related trades workers	0.040	0.176	0.164	0.767	1.194	0.910	1.440	0.891	1.221	0.702
73 Handicraft and printing workers	9.164	0.186	0.220	0.539	1.276	0.900	0.791	0.724	1.186	0.570
74 Electrical and electronic trades workers	4.682	0.165	0.234	0.866	1.367	1.075	1.949	1.473	1.525	1.027
75 Food processing, wood working, garment and other craft	0.720	0.114	0.085	0.749	0.788	0.545	0.314	0.798	0.869	0.544
81 Stationary plant and machine operators	1.120	0.114	0.137	0.299	0.922	0.657	0.820	0.831	1.074	0.659
82 Assemblers	2.721	0.127	0.101	0.105	0.916	0.704	1.135	0.661	0.999	0.536
83 Drivers and mobile plant operators	3.241	0.140	0.171	0.644	0.847	0.591	1.198	1.063	1.266	0.674
91 Cleaners and helpers	0.920	0.021	0.065	0.223	0.147	0.083	0.194	0.609	0.670	0.377
92 Agricultural, forestry and fishery labourers	7.683	0.027	0.021	0.418	0.297	0.279	0.164	0.037	0.368	0.071
93 Labourers in mining, construction, manufacturing and transport	7.843	0.089	0.120	0.501	0.740	0.478	0.554	0.753	0.974	0.507
94 Food preparation assistants	2.321	0.075	0.095	0.871	0.442	0.356	0.182	0.779	0.884	0.737
95 Street and related sales and service workers	6.002	0.219	0.030	0.000	0.957	1.157	0.000	0.000	0.000	0.000
96 Refuse workers and other elementary workers	1.561	0.075	0.128	0.428	0.450	0.499	0.837	0.979	1.062	0.604
Mean		0.114	0.131	1	1	1	1	1	1	1
Minimum		0.000	0.000	0	0	0	0	0	0	0
Maximum		0.219	0.301	2.291	1.740	2.104	2.135	2.109	1.551	1.940

Notes:

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

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

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

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OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

"GRADUATE JOBS" IN OECD COUNTRIES: ANALYSIS USING A NEW INDICATOR BASED ON HIGH SKILLS USE

Golo Henseke and Francis Green

Centre for Learning and Life Chances in Knowledge Economies and Societies (LLAKES)

UCL Institute of Education, University College London

A recurring issue for education policy-makers is the labour market effect of the long-term global mass expansion of higher education, particularly on what is a "graduate job". The traditional assumption is that graduate jobs are virtually coterminous with professional and managerial occupations. A new indicator of graduate jobs, termed ISCO(HE)2008, is derived using task-based data drawn from the The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The new classification shows that several jobs in ISCO major group 3 "Technicians and Associate Professionals" are also classed as graduate jobs in many countries. Altogether, 27.6% of jobs are classified as graduate jobs in the 15 OECD country-regions for which we have data. Considerable variation in the proportion of graduate jobs is found across industries and countries and in the short period from 2011 to 2013, the proportion of graduate jobs has become more diverse across countries.

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1. Introduction

A recurring issue for education policy-makers is the labour market effect of the long-term global mass expansion of higher education. Across North America, Europe and Asia, school leavers' educational aspirations have risen to the point that they are now more likely than not to proceed to tertiary education, and the consequences have for the last two decades been seen in the growing stocks of tertiary-educated labour in the workforce. Between 2000 and 2011 the proportion of the population (35-64 years old) with tertiary education had grown from 22% to 32% on average across OECD countries (OECD, 2013a), and the European Union has declared a common goal to reach a proportion of at least 40% graduates in the age-group 30-34 year-olds by 2020 (European Commission, 2014). By contrast, while the traditional destinations for graduates in professional and managerial occupations have expanded simultaneously, this has been to a much lower extent (Handel, 2012). If the large and ongoing rise of high-educated workers is to yield growth dividends and to meet new graduates' expectations for good jobs, the question arises: where are the jobs in which these graduates can adequately utilise their skills?

One way in which this question is typically addressed directly is through the lens of the concept of the "graduate job", and we take this approach here. Yet any such investigation begs the question as to how such jobs are defined and measured. Although the traditional notion of a "graduate job" in management or the professions lingers on in the language of elite HR recruiters from high-ranking universities and in the expectations of many students, we argue that there is need for a modern indicator which embraces a broader set of occupations and tasks, respecting the fact that, alongside the massification of higher education, there has been a prolonged period of skill-biased technological and organisational change and a globalisation of capital.

This approach to understanding graduate labour demand complements the conventional economic approach that focuses on the economic return to higher education. While in most countries the graduate wage premium has been maintained through recent periods of HE expansion (OECD, 2014), there is some evidence of growing heterogeneity in the returns, linked in part to overqualification[1] (Green and Zhu, 2010; Figueiredo et al., 2013). Below we use estimates of the wage premium to show the validity of a new classification in an international context, and how it compares with alternative traditional indicators.

For a modern graduate job indicator to be useful for understanding graduate labour markets around the world, it is essential that it be rooted in the character of the job's skill requirements, whilst taking the relative national position of graduates on the labour market into account. In this paper we develop and analyse a theoretically motivated, transparent and replicable classification of graduate jobs, using data from The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The Survey of Adult Skills (PIAAC) is an international survey of key skills, skills use and socio-economic background of the adult populations aged 16-65 years. Using a method developed and validated using the British Skills and Employment Surveys (Green and Henseke, 2014), we combine self-reported information on the qualifications needed to do the job competently with rich data on skill use at work and further drivers of country-specific higher education demands, to derive an indicator of graduate jobs. As our approach classifies ISCO 2008 minor groups, the classification can be easily applied within countries to other general purpose surveys where occupation is coded. It can also be used to deepen understanding of graduate labour demand from an international perspective.

The resulting classification - which we term "ISCO(HE) 2008" - displays a varied, country-specific picture of graduate jobs. The indicator shows that higher education is required for a considerable range of jobs, going beyond the traditional ones. The classification is thus quite distinct from the existing one, termed ISCO(1&2), which determines, through expert judgements, that only occupations in major groups 1

1. This term is synonymous with the term "overeducation" used by many authors.

and 2 qualify as graduate jobs, and then not quite all of them – amounting to 21.2% of jobs across the 15 OECD country-regions (including Cyprus[2]) in the purview of the Survey of Adult Skills (PIAAC). By contrast, we find that 27.6% of jobs across can be classified as graduate jobs, according to ISCO(HE) 2008 which is based on statistical analysis of high skills use.

The prevalence of graduate jobs varies considerably across countries, with relatively low proportions of graduate jobs in the Czech Republic, Japan and Germany, and relatively high proportions in Poland, the Netherlands and Norway. We find that these cross-national differences, over and above the industry structure and firm-size composition, are consistent as expected with differences in the relative qualities of graduates and other skilled labour. We also find that graduate job prevalence within countries is positively associated, as expected, with industry R&D intensity, firm size and public ownership.

This paper is structured as follows. In section 2 we develop the concept of graduate jobs, and put forward a simple framework for the determination of graduate jobs. Section 3 considers existing graduate jobs classifiers, and reviews the existing internationally comparative literature. It then introduces the Survey of Adult Skills (PIAAC), and describes the key indicators used in the classification. We derive the classifier in section 4 and examine its construct validity in section 5. Section 6 presents our findings from analyses of the prevalence of graduate jobs. Section 7 concludes and discusses some limitations. Annex A shows the occupations classified as graduate jobs across countries.

2. Concept and theoretical framework

The concept of a graduate job

Following (Green and Henseke, 2014) we can think of a graduate job as being one where most of the skills used are usually acquired in the course of higher education, including many of the activities surrounding it, and in the course of ensuing or coterminous periods of work. Graduate skills are generally thought to comprise a combination of subject-specific professional skills, cognitive skills such as problem solving, knowledge creation, information-processing and management skills, as well as planning and people skills to mobilise others and oneself (Allen and Van der Velden, 2011; Barone and Ortiz, 2011). Following on from this concept, a graduate is deemed overqualified if working in a non-graduate job.

It is not straightforward to determine the timing, source and substance of skill acquisition. Graduate skills are the outcome of the entire history of skill formation since childhood (Heckman, 2007). Besides the skills acquired through formal education at universities and colleges, the broader higher education experience itself contributes to the development of graduate skills. Leaving home, travelling, potentially studying abroad and encountering other people with different viewpoints contribute to the individual skill set with potential productive value in the labour market. Higher education provides not only subject-specific skills but also helps to develop generic skills such as giving presentations, independent learning,

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2. Note by Turkey:

The information in this document with reference to “Cyprus” relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the “Cyprus issue”.

Note by all the European Union Member States of the OECD and the European Union:

The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

delivering written documents on tight deadlines, solving complex problems and efficient learning strategies (Jackson, 2014).

Work placement including employment, internship or charitable work, either part-time during the course or full-time afterwards, is another potential source of skill formation. Students learn to apply taught skills productively at the workplace. Study-related work placement is often seen as key to secure employment (Crebert et al., 2004). Yet the prevalence of work placements varies considerably across countries: according to one recent study, for example, British, Spanish and Flemish graduates gathered much less work experience during higher education than graduates from the Netherlands or Germany (Allen and Van der Velden, 2011).

Family, friends and social networks can also contribute to skill development during higher education. Family background contributes to skill formation, potentially throughout life (Björklund and Jäntti, 2012; Björklund and Salvanes, 2011). However, its biggest effects on individual development usually precede university studies and might thus be related to access to higher education (Heckman, 2007; Chowdry et al., 2013). This effect gives rise to suggestions that higher education is just a signal of higher abilities rather than a genuine source of skill development (Wolf, 2002), though the evidence for this is slim (Aakvik et al., 2010; Kautz et al., 2014). Nevertheless a concept of graduate jobs is more convincing if it can differentiate between skill use and credentialism.

Further, some high-level skills can potentially be acquired through other sources than higher education. High quality vocational education and training (VET) systems can provide alternative access to skills required to carry out complex jobs. Consequently, for many tasks vocationally-educated labour may have a relatively high degree of substitutability for graduate labour. It is widely held that the quality of vocational education and training varies considerably between countries and regions. Thus, in countries where the quality of higher education is high *relative* to the quality of substitutable high-end vocationally-trained labour, there is likely to be a greater demand for graduate qualifications for a given task composition of jobs. Consequently, the prevalence of graduate jobs will change with labour market institutions and features of the education and training systems that influence the relative quality and price of graduates.

Our proposed skills-focused concept of graduate jobs differs from alternative approaches which focus either on occupational prestige (Ganzeboom and Treiman, 1996; Macmillan and Vignoles, 2013), or more specifically on the professions (Milburn, 2009; Allen and Van der Velden, 2011) or, in line with human capital theory, on whether higher education is especially highly-valued within that occupation by the labour market (Cardoso, 2007; Gottschalk and Hansen, 2003; O'Leary and Sloane, 2014).[3] These alternative classifications overlap with ours: for example skills usage, occupational prestige and pay are usually higher for "professional" occupations and so these occupations will be classified as graduate jobs under all approaches. The different outcomes arise with other major groups (mainly, managers and associate professional/technical occupations). Yet in our approach, concentrating on the functional side of jobs, skills use, allows us to identify graduate jobs based on the tasks people carry out during their work and whether they require higher education to do so competently. This classification approach has the most direct connection to the theoretical concept.

The distribution and trend of graduate jobs: Theoretical expectations

The question posed in our introduction – the motivation for developing a modern graduate jobs indicator – concerned how labour markets have adjusted in the 21st century to the upskilling of labour forces around the world through the massification of higher education, alongside the ongoing rising

3. See Green and Henseke (2014) for a critique of these alternative approaches.

demand for high-skilled labour. There are concerns in both western and Asian nations that the supply of graduate labour is outstripping the numbers of graduate jobs (e.g. Cedefop, 2012). For example, the state of the United Kingdom graduate labour market has come under increased scrutiny recently (Elias and Purcell, 2013; Green and Henseke, 2014; O'Leary and Sloane, 2014). A better understanding of graduate jobs should help to inform policy makers about upcoming challenges.

Notwithstanding that technological and organisational change is partly endogenous in the long-run, depending on skills supplies and relative prices, we start from the presumption that the distribution and trends of graduate jobs will reflect demand. Theory implies that the demand for graduates depends, first, on the extent to which high skills are demanded in the economy and, second, on the extent to which higher-educated labour delivers high skills. Both these links could be expected to vary across countries/regions and over time.

The widespread shift towards high-skill jobs is not new; it has been ongoing for at least several decades (Handel, 2012). The main attributed global drivers have been technological and organisational changes, alongside the evolving global division of labour. The emphasis has mainly been on technological change (Acemoglu and Autor, 2011; Machin and Van Reenen, 1998; Van Reenen, 2011); ICT, especially, is held to have raised the productivity of graduate workers over the last 30 years or so. This skill-biased technological change (SBTC) is held to be the principle driver behind the growth in the demand for graduate labour.

Nevertheless, it is by no means certain that contemporary technological change is leading to an ongoing upgrading of jobs. An alternative contemporary and future scenario has been painted by certain commentators of a divergence of opportunities for graduate labour, with computerisation now leading to "digital Taylorism" and associated de-skilling of the bulk of graduate jobs, with only a minority of especially talented graduates from elite universities continuing to enjoy ever increasing favour in the labour market (Beaudry et al., 2013; Beaudry et al., 2014; Brown et al., 2011). Resolution of these contrasting predictions may only emerge as the future unfolds, but it remains useful to ask whether the distribution of graduate jobs in the current era is positively linked to technology, and work organisation.

While transferable technology is expected to be widely diffused, it is expected nevertheless that the pace of absorption varies according to the capacity of firms and their employees to absorb new techniques and processes (Zahra and George, 2002). Management skills and systems of work organisation are among the important factors influencing such absorptive capacity. Regions that become stuck in "low-skills" equilibria can exhibit sustained low levels of skills demand, while other regions move ahead (Giguère and Froy, 2009). Quintini (2014) has found substantive cross-country variation in skills utilisation levels, associated in part with variations in labour productivity.

Some cross-national/cross-regional variation in the demand for high-level skills, and thereby in the prevalence of graduate jobs, could therefore be expected. Equally SBTC leads to the expectation of a generalised increase over time in the prevalence of graduate jobs, though if counter-tendencies come to predominate the opposite expectation arises.

A second factor in the distribution of graduate jobs is the relative cost and availability of alternatively-educated, substitutable, high-skilled workers. At least some of the high-level skills could be acquired through vocational and work-based learning routes. What matters, therefore, is the quality of graduate labour relative to potential substitutes. In a country where high-skilled substitutable vocational labour is available, employers design fewer jobs *ceteris paribus* as graduate jobs. We expect there to be cross-country differences in the mapping from job skills to educational demands, reflecting the relative qualities and costs of graduate and vocationally-educated labour. This expectation contributes an additional reason for international variation in the use of graduate labour.

3. Data and skills use indicators

Existing indicators

Existing studies utilise diverse principles for deriving indicators of graduate jobs. Most frequently used is the simple traditional classification based on being coded in one of the first two major ISCO groups – Managers or Professionals. To recognise the need to modernise this classification by going beyond the traditional approach, recourse is sometimes made to the idea that graduate jobs are defined by what graduates do. While this approach can be delivered in a subtle way that takes account of the age structure of occupations, and allows for exceptions or niches to be identified as graduate jobs (e.g. Elias and Purcell, 2004), at least in its simplest form this supply-driven approach is subject to the criticism that it is tautological and of limited use for analytical purposes. To replace such an approach with a conceptually more satisfactory demand-driven perspective, expert-based classificatory mechanisms may be available (e.g. Elias and Purcell, 2013, for the United Kingdom) which deploy knowledge about the tasks involved in occupations to make judgements about whether they require graduate-level skills. Some of this knowledge can be gleaned from detailed job titles. Yet, expert-based classification methods remain somewhat subjective, are hard to replicate and update, and could not be extended to an internationally comparable classification except perhaps at enormous cost.

A further method has been to identify occupations as graduate jobs when there is evidence that graduates are offered a premium within that occupation (e.g. Gottschalk and Hansen, 2003). Rooted in an assumption about the competitiveness of labour markets where scarce skills are rewarded when demanded, this method has the merit of avoiding use of self-reported job assessments. Yet it has the disadvantage that it relies on gaining unbiased estimates of within-occupation returns, which is rendered nearly impossible by the fact that occupational selection and human capital returns are closely interlinked. Moreover, the method cannot then be utilised as a tool for analysing wage returns without, again, risking tautology. The wage-returns approach would also be questionable when applied in an international comparative perspective, because there is a large international diversity in the effects of labour market institutions on wages. Among existing indicators, only the traditional indicator and the supply-driven methods lend themselves to an international approach. But since neither of these seems remotely adequate in the context of the modern world, with changing skills demands rendering the traditional measure out of date, and rapidly growing graduate stocks covering supply-driven indicators with a thick layer of tautology. A better method is warranted, and one that does not simply add on further major occupational groups indiscriminately without considering the concept of what a graduate job is.

Before proceeding to our improved approach, it is worth noting that one or other of the above principles for defining graduate jobs also underpins some of the indicators of overqualification found in the literature. The negative consequences of overqualification and skills underutilisation such as wage penalties, reduced job satisfaction and potential reductions in further training are well documented (Leuven and Oosterbeek, 2011; Quintini, 2011a). However, relatively little is known about graduate skills utilisation from a comparative cross-country perspective. The lack of consistent international data sources on skill utilisation has made it for some time impossible to validly compare the incidence of underutilisation across multiple countries. For instance, the European Working Conditions Survey (EWCS) has started collect information on skills utilisation from 2005 onwards. But this data has to our knowledge not yet been applied to study the labour market of university graduates across (European) countries (see Quintini, 2011b for an analysis of skills mismatch in the employed labour force in general).

A study by (Croce and Ghignoni, 2012) uses the European Labour Force Survey to investigate overqualification amongst graduates who hold a degree of higher education in Europe between 1998 and 2006. The study relies on the so-called “statistical” measure of overqualification, where required education is given by the modal or median or mean education level held by workers in each occupation. Graduate mismatch was worst in the Czech Republic, Germany and Austria with more than half of the graduate workforce in non-graduate jobs. Romania, Finland and Luxembourg were on the other end of the scale with a proportion of about 25% of mismatched graduates. The values for, for instance Italy, Spain and the United Kingdom were in between the extremes. In all, about 37% of graduates were overqualified in Europe at the turn of the millennium; the proportion slightly dropped to 35% in the middle of the 2000s. The authors conclude from a multivariate country-level analysis that overqualification reacts mostly to short-term business cycle fluctuations.

Yet so-called "statistical" measures of over-education have received much criticism (Hartog, 2000). They are based, not on skill requirements, but on the qualifications of the people doing the job. Educational expansion and the distribution of educational achievements in the workforce vary considerably across countries (Green, 2013). Therefore, the statistical method is poorly suited for international comparisons of trends in overqualification.

The REFLEX (Research into Employment and Professional Flexibility) survey has so far been the richest source of internationally commensurate information on labour market outcomes of graduates. Collected in 2005, REFLEX sampled data on the labour market trajectories of tertiary education graduates from 1999/2000 in 16 European countries and Japan. It built on an earlier survey over 12 countries, conducted in 1999-2000 entitled CHEERS (Careers after Higher Education: a European Research Study). REFLEX provides detailed information on multiple dimensions of job mismatch, the higher education experience, labour market history, current employment and the parental background (Allen and Van der Velden, 2011). A small but hugely informative literature has evolved around this study and has provided so far the most comprehensive insights into the state of graduate labour markets in Europe and beyond. Further international surveys based on REFLEX were later conducted in Eastern European countries ("HEGESCO") and in Latin America ("PROFLEX").

In all, 26% of the graduates were overqualified six months after they finished higher education according to the REFLEX data, but there was substantial variation between countries. In Spain, Italy and the United Kingdom more than 38% of recent graduates worked in jobs that did not require higher education, compared to less than 20% in France, Switzerland, Germany and Portugal. Five years after graduation the proportion of overqualified graduates had generally shrunk. The drop in overqualification was most pronounced in countries with initially high levels of mismatch. Germany, Switzerland and Japan were characterised by the highest persistency in average overqualification (Verhaest and Van der Velden, 2013). Variation in overqualification has been variously attributed to imbalances between the supply and demand for highly skilled labour, the quality and orientation of study programmes, skill heterogeneity within occupations, and the scarring effect of entering the labour market during a recession (Barone and Ortiz, 2011; Verhaest and Omey, 2009; Verhaest and Van der Velden, 2013).

Though the comparison is imperfect because populations did not entirely overlap, the figures for the proportions overqualified differed markedly from those reported by (Croce and Ghignoni, 2012). Not only was the incidence of overqualification lower in the REFLEX study despite applying to a younger population, but also the country ranking had swapped with graduates from Germany, Austria and the Czech Republic reporting the lowest proportion of overqualification. Such measurement diversity highlights the need for high quality data to track educational mismatch, especially across countries.

Overqualification is related to the concept of skills underutilisation. Overqualified workers are thought to utilise less of their skills than adequately matched graduates. However, the relation is far from perfect (Green and Zhu, 2010). The incidence of skills underutilisation varied between around 20% in Norway and Finland to almost 35% in Spain, the Czech Republic and the United Kingdom in the REFLEX data – roughly confirming the country ranking for the incidence of overqualification (Allen and Van der

Velden, 2011). The country ranking also holds when horizontal mismatch, i.e. the gap between field of study and the required job-specific skills, to the exploration of mismatch, was added to the picture.

While REFLEX provides arguably the best analyses to date regarding the international deployment of recent graduates, it is not really suitable for defining a graduate jobs classifier of occupations. Not only is it now a decade old, its findings apply only to the jobs of recent graduates, not to jobs in general. It could define, on an individual level, whether workers perceive themselves to be in graduate jobs, using the self-reported single-item measure of whether a graduate-level qualification is required for the job. It is argued elsewhere that workers are generally well suited to assess the skill and qualification requirements of their job.[4] But responses to a single item will carry errors, affected by individual's self-esteem or facets of the job that are unrelated to skills usage. If unrecognised, these errors would be conveyed to the resulting indicators. An indicator of whether graduate skills are required in an occupation should aim to be purged of such errors.

In the next section we develop such an indicator. Similar to methods in health economics which rid self-reported health from reporting error, the procedure uses indicators of high skills use to uncover the variation in the qualification requirements that are attributable to differences in high skills demands. The classification captures the use of graduate skills independently of the sources of skills. It does not rely on assumptions about the link between higher education and wages within occupations. The method avoids the use of hard-to-replicate expert judgements and deploys an observer-neutral classification procedure, based on relatively simple statistical classification methods, while not relying on single survey item responses. The result is a transparent and replicable procedure, and an indicator that is flexible enough to allow for country differences in graduate jobs and which can be consistently amended over time as technologies and workplaces evolve.

The Survey of Adult Skills (PIAAC)

We use data from The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), which is an international survey that has been carried out in 33 countries and economies (OECD, 2013b). The fieldwork for the first round was conducted between 2011 and 2012 in 24 countries. The sample population is the respective national adult population aged 16 to 65 years. Overall, more than 120 000 people were assessed in three proficiency domains – literacy, numeracy and problem solving skills in "technology-rich environments" – and interviewed on topics covering use of skills at work and at home, the work experience, continuing training, and personal characteristics such as qualifications, family background or health. Around 5 000 interviews were carried out per country. A harmonised sampling procedure, a standardised questionnaire and shared classifications for industry, qualification and occupations ensured high comparability across countries.

The extent of data anonymisation in the public-use files differs from country to country, and affecting access to disaggregated occupation codes. At the time of the writing, only the German data has been made available as restricted use-file (Perry and Helmschrott, 2014). In all, we have information on detailed occupation codes for 15 countries: Belgium, Cyprus,[5] the Czech Republic, Denmark, France, Germany, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Spain and the United Kingdom. This country selection covers various typed of education and training systems with varying trajectories in higher education. Data for Belgium and the United Kingdom are not nationally representative, but cover in case of the former Flanders and in the latter England and Northern Ireland.

4. There is no evidence of a substantial, systematic, bias in workers' self-assessments of their jobs, but there is a possibility of a small gender bias (Green and James, 2003).

5. See note 2.

Because of data quality concerns, we excluded the Russian Federation survey data from our analysis (OECD, forthcoming).

The Survey of Adult Skills (PIAAC) uses a complex sample design to achieve representativeness for the national target populations. To adjust for the sampling procedure, in the analyses that follow we make use of the provided probability weights to derive the correct standard errors for parameter estimates.

Skill indicators

The Survey of Adult Skills (PIAAC) data have already been utilised to derive novel measures of skills mismatch among all employees (Allen et al., 2013; Pellizzari and Fichen, 2013). In contrast to these studies, we are specifically concerned here with the utilisation of graduate skills in the labour market.

The indicator will classify minor group (3-digit) occupations, defined by the International Standard Classification of Occupations 2008 (ILO, 2012), according to whether they are graduate or non-graduate jobs. ISCO08 provides a consistent and internationally comparable framework to classify occupations, consisting of four hierarchical levels with increasingly detailed occupational groups. At the most detailed level it differentiates between 436 unit groups, which are structured into 130 minor groups and 43 sub-major groups. The top level is formed of 10 major groups: Armed Forces Occupations; Managers; Professionals; Technicians and Associate Professionals; Clerical Support Workers; Services and Sales Workers; Skilled Agricultural, Forestry and Fishery Workers; Craft and Related Trade Workers; Plant and Machine Operators and Assemblers; and Elementary Occupations.

ISCO08 groups these jobs according to the required skill level and skill specialisation as assessed by occupational experts. Jobs at the highest skill level usually demand high-level non-routine cognitive tasks such as problem-solving, decision-making and creativity drawing on an extensive knowledge base. According to ISCO documentation, most occupations in major group “1 Managers” and all occupations in “2 Professionals” utilise these high level skills. Since these skills are assumed to be normally acquired through higher education, these two groups are conceived as defining graduate jobs (European Commission, 2014). This classification forms a benchmark against which we will (below) compare our modern indicator of graduate job.

Before proceeding, it is important to note two limitations that potentially apply to any occupation-based classification of graduate jobs. Firstly, we need to assume that jobs within the basic unit (in this case, minor groups) are sufficiently homogenous in terms of skill levels to meaningful classify them as either graduate or non-graduate. Secondly, there is potential for measurement error in the occupational coding in any survey (Mathiowetz, 1992; Sullivan, 2009). Respondents might misreport their job titles or give ambiguous information, and there is the potential for ambiguity in the allocation of job titles to occupation. The problem could be exacerbated with international surveys as coding practices vary between countries. The distinction between managers and administrators (major groups 1 and 4) or professionals and associate professionals (major groups 2 and 3) can, for instance, be fuzzy (Handel, 2012). The PIAAC consortium has established safeguards at various stages of the survey design to ensure high quality and consistent occupational classification across countries. Members of the national survey teams received dedicated training to code occupations in the ISCO08 framework. Further, at least 50% of jobs had to be double coded. Potential coding conflicts were resolved by a member of the PIAAC consortium. The resulting distribution of occupations was checked against national labour force data. All participating countries passed the minimum quality criteria (OECD, 2013c).

The selected indicators are motivated by the concept of graduate jobs outlined in the section above. We have constructed multiple variables which will form the ingredients of the classification:

1. *Degree essential*: Employed respondents in The Survey of Adult Skills (PIAAC) are asked to assess the qualification required to get their current job. Because there may be credentialism – where a qualification is asked for, but not necessary for doing the job, respondents are also asked whether the required qualification is also needed to perform the job satisfactorily. The information is dichotomised according to the coding scheme in Table 1. Generally, higher education is required if a qualification at ISCED5A level or above is appropriate for the job. In cases where a master or doctoral degree is necessary to get but not essential to do the job, it is plausible to assume that a shorter higher education course will nevertheless be required to perform the job tasks satisfactory.[6,7]

Table 1. Coding of self-reported higher education requirements on the job

Higher education required to get the current job	Also needed to perform the current job	Higher education required to do the job
ISCED 6	Yes/ No	Yes (==1)
ISCED5A - Master	Yes/ No	Yes (==1)
ISCED5A - Bachelor	Yes	Yes (==1)
	No	No (==0)
<=ISCED5B	Yes/ No	No (==0)

2. *Degree essential (similar jobs)*: ISCO groups similar jobs in terms of required skill level and skill specialisation together. We exploit this construction principle to derive an indicator of the demand for higher education in jobs similar to the worker's current position. Observations within the same minor group (3-digit occupation) in the same country define the neighbourhood of similar jobs. The indicator is calculated as the average demand for higher education in the neighbourhood. Formally,

$$DN_i = \frac{1}{K(i)} \sum_{k=1}^{K} D_{k(i)},$$

where $k(i)$ described the set of observations within the same minor group and same country as job i, $D_{k(i)}$ captures the need for higher education to carry out job k in the neighbourhood of respondents i's job, and, finally, DN_i, represents the average demand for higher education in the neighbourhood of job i. The variable captures differences in the need for higher education over and above job tasks.

3. *3+ years of experience required.* Some graduate jobs potentially require prior work experience in addition to formal education. For certain high-skill jobs, for instance managerial positions, it is essential to have command over some firm-specific or industry-specific knowledge to do the job competently. Participants in The Survey of Adult Skills (PIAAC) report on how much related

6. There is an idiosyncrasy in the British data with respect to the relevant ISCED codes. Higher education is not further differentiated but instead subsumed into one category. We assume that a Bachelor degree will suffice to get most of the graduate jobs in Britain and treat the category accordingly within our coding scheme.

7. In Denmark and Flanders (Belgium), there were some graduate level jobs in sub-major group "95 Street and Related Sales and Service Workers". A closer inspection of the industry codes and the skill use on the job suggests that, despite the precautions by the PIAAC consortium, the occupations were most likely miscoded. Generally, we have excluded 127 observations in major groups 5-9 from the sample that stated higher education requirements and saw a substantial need of degree requirements in similar jobs on the ground of potential miscoding.

work experience is needed to get their current job. The variable is dichotomised and receives the value 1 if 3 or more years of experience are necessary to get the respondent's current job.

4. *Information processing skills.* The growing use of cognitive and people skills at work is often seen as key driver of the increasing demand for graduates. It is this combination of generic skills that sets graduate jobs apart from more routine jobs. Higher education provides the holder with a comparative advantage to perform these tasks effectively (Autor and Handel, 2013; Green, 2012). The Survey of Adult Skills (PIAAC) background questionnaire covers a comprehensive list of skill use at work in areas such as literacy (reading and writing documents), numeracy (calculation of budgets, usage of simple algebra), the level of computer use, problem solving, organising (own work and others), and communicating (presenting, teaching). In addition, the published Survey of Adult Skills (PIAAC) data files include broader skill use scales derived from combinations of a selection of the single items. The scales are derived by the PIAAC consortium using Item Response Theory. The single items capture the frequency with which each task is performed, ranging in four steps from "Less than once a month" to "Every day".

   We deploy a subset of the task items, a selection of the provided skill use scales and some related variables. Each variable is defined as a binary variable which is one if respondents perform a specific task at least weekly (for single task items) or fall into the highest category of the included PIAAC skill use scale, and zero otherwise. The items cover high-level numeracy, reading and writing as well as regular complex problem solving and high-level computer use.

5. *Orchestration skills.* Using the same principles, information on regular teaching, presenting, advising, influencing, negotiating, planning others and supervisor status are used to summarise the use of orchestration skills.

6. *Job autonomy.* Finally, we include a measure of job autonomy into the construction of the classification. Graduate jobs are thought to give the individuals a certain level of discretion over facets of the job. Autonomy is both a normative measure of graduates' job quality (Boccuzzo and Gianecchini, 2014; McGuinness and Sloane, 2011), but also a contributor to the skill requirements of the job. Planning one's own work, prioritising tasks, and regulating the pace of work requires skills. In all, it is an additional dimension that distinguishes graduate jobs from non-graduate jobs, which impose stricter routines and offer less discretion. The Survey of Adult Skills (PIAAC) data include items on self-planning and work flexibility. Work flexibility is assessed by four items on different facets of job autonomy with responses ranging from 1 "not at all" to 5 "to a very high extent". Job autonomy describes discretion over various job domains and is thus measured by a summary score that covers information on how flexible workers can set their tasks, determine how the work is done, the speed of work and working hours as well as the need to plan their own work activities and time. The single indicators are again defined as binary variables with values one if respondents report very high levels of discretion for each flexibility item or state that self-planning skills are required at least on a weekly basis.[8] The final score is calculated as the average over the included items.

Table 2 summarises the descriptive statistics of these indicators for the pooled sample of 15 countries.

8. With Cronbach's alpha for the resulting scale of 0.75, one could plausibly regard this scale as capturing a single latent construct of "high autonomy".

Table 2. Summary statistics (N=49 986)

Variable	Mean	Standard deviation	Min	Max
Degree essential	0.226	0.418	0	1
Degree essential (similar jobs)	0.226	0.287	0	1
3+ years of experience required	0.208	0.406	0	1
Information processing skills				
1. High level numeracy	0.153	0.360	0	1
2. High level reading	0.181	0.385	0	1
3. High level writing	0.180	0.384	0	1
4. Complex problem solving	0.341	0.474	0	1
5. High level computer use	0.128	0.334	0	1
Orchestration skills				
6. Regular teaching	0.286	0.452	0	1
7. Regular presenting	0.131	0.337	0	1
8. Regular advising	0.552	0.497	0	1
9. Regular influencing	0.472	0.499	0	1
10. Regular negotiating	0.352	0.478	0	1
11. Regular planning others	0.305	0.460	0	1
12. Supervising	0.138	0.345	0	1
Job autonomy scale	0.354	0.259	0	1
13. High level discretion: tasks sequence	0.208	0.406	0	1
14. High level discretion: how	0.201	0.401	0	1
15. High level discretion: speed	0.186	0.389	0	1
16. High level discretion: working hours	0.092	0.289	0	1
17. Self-planning	0.693	0.461	0	1
18. Self-organisation	0.742	0.438	0	1

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Overall, we have close to 50 000 observations available to derive the classification. About 23% of respondents in the sample work in self-reported graduate jobs. A fifth of the respondents work in jobs that required long prior work experience. Complex problem solving is the most common required information processing skill; a bit more than a third of the respondents have to think about problems that require 30 minutes or longer to come to a solution on a weekly basis. High level computer use is the least frequent item among the cognitive skill use indicators. Many people might use computers but mostly for relatively low-level tasks. Among orchestration skills, regular advising and influencing were the most common items: about half of the sample uses these skills at least on a weekly basis at work. Potentially noteworthy, about 14% of job-holders have supervisor responsibilities. The mean value of the autonomy scale is 0.35. Around a fifth of respondents reported high level discretion over task sequence how work is done. Working hours was an area over which workers were least likely to have significant autonomy. In contrast, more than two-thirds of the workers in the sample planned their own work activities and again more than two thirds organised their own time.

This list of skill use measures is neither exhaustive nor will every graduate job necessarily demand high levels of each variable. We argue, however, that the defined variables capture different aspects of graduate jobs which, in combination, capture the non-routine cognitive and interactive-intensive characteristics that distinguish graduate from non-graduate positions.

To capture further systematic differences in the propensity for higher education demands over and above skills, we also consider age, age square, gender and country dummies covariates as additional covariates.

4. Constructing ISCO(HE) 2008

Classifier

The classification procedure builds on our earlier work (Green and Henseke, 2014). The main idea is to uncover the variation in the self-reported higher education requirements that can be attributed to the variables capturing high skills use and other systematic job and country-specific factors. The properties of the resulting classification are validated in section 5. We pool the available data into one international dataset.

The classifier is derived through a three-step procedure. Firstly, we estimate a latent "higher education requirement" score from the individual measures. Next we average the latent variable across minor group-country cells. And finally, we calculate for each country separately a threshold for the higher education requirement score, above which higher education is appropriate to do the job.

First, we estimate the following model:

$$\Pr(HE_i) = \Phi\big(\beta_j JSR_i + \gamma_j DR_{ij} + \delta_j X_i + u_j + \varepsilon_{ij}\big),$$

by running a probit regression of the self-reported graduate job indicator HE_i of individual i on the job skills requirement variables, JSR_i, the degree requirements in similar jobs DR_{ij}, which change by country j, socio-demographic controls X_i, and country fixed effects u_j. All parameters are allowed to differ between countries. Table 3 reports the average marginal effects of the job skills requirement variables on the latent demand for higher education over all included countries.

The probit regression represents an underlying latent variable model that captures the higher education requirements of a job. The model allows for country-specific mapping of job skill requirement to educational demands and other systematic differences in the prevalence of graduate jobs over and above the observed job skills. The objective is to retain the variation in the latent variable that is explained by the observed variables. Random reporting error is captured by the error term ε_{ij}.[9]

9. It is assumed, here, that self-reported educational requirements and the high skills use variables are not simultaneously affected by the same unobserved determinants, such as reporting behaviour or exerted work efforts.

Table 3. Average marginal effects of job requirement skills on latent higher education demands

Variable	AME/SE
3+ years of experience required	0.239***
	(0.0205)
High level numeracy	0.170***
	(0.0217)
High level reading	0.296***
	(0.0209)
High level writing	0.0296
	(0.0211)
Complex problem solving	0.249***
	(0.0181)
High level computer use	0.248***
	(0.0232)
Regular teaching	0.0385
	(0.0209)
Regular presenting	0.157***
	(0.0257)
Regular advising	-0.00878
	(0.0203)
Regular influencing	0.0980***
	(0.0215)
Regular negotiating	-0.0316
	(0.0207)
Regular planning others	-0.0181
	(0.0206)
Supervising	0.116***
	(0.0239)
Job autonomy scale	0.216***
	(0.0354)
Observations	49 986

Notes: Standard errors statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Generally, degree requirements increase with higher information processing and orchestration skills as well as with job autonomy. Information processing skills receive the largest weight. But job autonomy, professional communication skills (presenting, influencing) and supervisor status emerge as further important contributor to higher education requirements.

Differences in the demand for higher education over and above the observed job requirements are captured jointly by the degree requirement in similar jobs, the demographic controls and country effects. As argued these variables will reflect cross-national differences in the relative perceived quality and prices of graduates. To illustrate cross-country differences in the prevalence of graduate jobs, we predict the latent higher education requirement scores for jobs in occupational major groups one to four based on the observed degree requirements in similar jobs, age and gender in this group whilst job skills requirement are held constant at the sample means. Major groups one to four includes those jobs that potentially require higher education to be carried out effectively. The resulting figures will give country-specific estimates of the perceived relative quality of graduates. The calculating uses the provided survey weights to derive representative values. See Table 4 for the estimates.

Table 4. Adjusted mean demand for higher education at given job skills requirements over countries/ economies

Country/economy	Effect
Belgium (Flanders)	-0.524
Cyprus*	-0.356
Czech Republic	-0.495
Denmark	-0.597
France	-0.517
Germany	-0.667
Italy	-0.475
Japan	-0.515
Korea	-0.581
Netherlands	-0.445
Norway	-0.544
Poland	-0.306
Slovak Republic	-0.564
Spain	-0.486
United Kingdom (England/ Northern Ireland)	-0.599

Notes:

* See note 2.

Predicted graduate skills requirement score for jobs in major groups 1 to 4 with all skills use items set to the sample mean and non-task variables at their observed value. Calculation using the provided survey weights.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

According to the estimates, the perceived relative quality of graduates over groups at the nearest substitutable level of qualification is smallest in Germany, the United Kingdom (England/Northern Ireland) and Denmark. At a given level of job skills, there was a clearly lower propensity to demand higher education for a given job compared with the other countries in the sample. In contrast, graduates in the Netherlands, Cyprus[10] and Poland seem to have a relatively large perceived advantage over the closest educational groups to perform complex jobs.

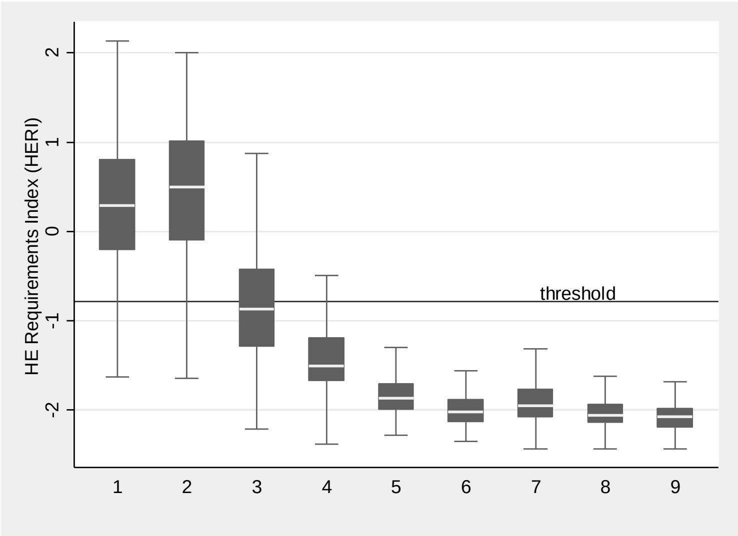
Next, we predict the *higher education requirements* as a weighted average of the explanatory job skill requirement variables and the non-task items with the item weights given by the estimated probit coefficients. As a first check, we found that almost 75% of the variation in the resulting *higher education requirements* score is explained by the ISCO08 minor groups, and that allowing for additional country differences increases the explained variance by only 2.8 percentage points. In other words, overall graduate skills requirements vary substantially between occupations and these patterns are very similar across countries.

In the second step, we average the score across minor group-country cells. For cells with fewer than four and no observations, we impute the resulting index with the average value from the 2-digit occupation. This affects 23% of all minor group-country cells. There is the risk that we impute from overly coarse occupational groups that do not properly reflect the educational requirements for the subsumed

10. See note 2.

minor-groups. However, further analysis shows that 2-digit occupations explain the variations in higher education requirement index well. In fact, the differences in explained variance compared to the full set of minor groups is only about five percentage points. In all, the procedure helps to reduce noise in the final classification. The distribution of the resulting Higher Education Requirement Index (HERI), illustrated in Figure 1, varies clearly across major groups. It is generally highest, as expected, among Managers (1) and Professionals (2), with Technicians and Associate Professionals (3) somewhat lower. Nevertheless, there are stark variations within the broad groups.

Figure 1. Box plot of the higher education requirement index by ISCO major groups 1-9 (excluding outliers and armed forces)



Notes: The box plot displays the distribution of the higher education requirement index. The upper and lower edges of a box represent the 75% and 35% Quartile, respectively. The median is given by the horizontal line within each box. The distance from the upper to the lower edge gives the Interquartile Range (IWR); a measure of dispersion. Finally, median plus and minus 1.5 IQR determine the position of the whiskers. Outliers are not reported. Data covers all 15 countries/economies.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

In the final step, we run a k-medians cluster analysis in the pooled sample to partition jobs into a graduate and non-graduate group. The K-medians algorithm is more robust against outliers than the similar, well-established, K-means algorithm (Everitt et al., 2001). We impose a two-cluster solution. The algorithm assigns occupations to a cluster by minimising the distance between the occupation-specific HERI value and the cluster's centre. All occupations with a HERI score above the derived threshold are labelled "graduate jobs", whereas occupations below the threshold are referred to as "non-graduate" jobs. The resulting cut-point between graduate and non-graduate jobs is at -0.781. Its relative position is displayed in Figure 1.

Description of classification outcome

We term the resulting classification *ISCO(HE) 2008*. Across all country-regions, it results in 27.6% of jobs in the employed workforce being classified as graduate jobs.

This section will provide details, discusses potential idiosyncrasies between countries and examine variations in the relative quality of graduates as source for cross-national differences. The distribution of HERI by country and the proportion of graduate level minor groups are summarised in Table 5.

Table 5. Distribution of the higher education requirement index, the threshold between non-graduate and graduate occupations and the proportion of graduate level minor groups by country/economy

Country/economy	Number of minor groups	Proportion of graduate level minor groups (%)	Graduate skills requirement index		
			Min	Median	Max
Belgium (Flanders)	122	27.0	-2.208	-1.532	1.476
Cyprus*	121	47.1	-2.074	-1.079	1.881
Czech Republic	121	28.1	-2.256	-1.749	2.172
Denmark	126	34.1	-2.159	-1.457	1.599
France	125	35.2	-2.315	-1.656	1.616
Germany	121	31.4	-2.561	-1.823	1.733
Italy	124	41.9	-2.421	-1.175	2.137
Japan	124	33.9	-2.119	-1.526	1.723
Korea	125	38.4	-2.248	-1.265	1.745
Netherlands	120	34.2	-2.292	-1.543	1.408
Norway	121	40.5	-2.205	-1.632	1.577
Poland	125	46.4	-2.070	-1.153	1.920
Slovak Republic	123	36.6	-2.195	-1.517	1.813
Spain	124	39.5	-2.289	-1.301	2.002
United Kingdom (England /Northern Ireland)	121	38.8	-2.434	-1.546	1.409

Note: * See note 2.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The proportion of graduate level minor groups varies between 27% in Belgium (Flanders) and 46% or above in Cyprus[11] and Poland. Compared to the country-specific HERI distribution, the threshold between non-graduate and graduate occupations is relatively low in Poland, Cyprus[12] and the Czech Republic, and highest in Germany, the Netherlands and England/Northern Ireland. In other words, higher education is required for a narrower, potentially more skill intensive set of jobs in the latter countries, whereas in the former group higher education is appropriate for a wider range of jobs.

The full list of graduate and non-graduate occupations in each country is given in Annex A. While for most occupations the classification is decisive, at the margins there is ambiguity over whether higher education is appropriate to do the job competently or not. The ambiguity is hard, perhaps impossible, to avoid. The difference in HERI between the highest scoring non-graduate and lowest scoring graduate jobs is negligible; thus the step from non-graduate to graduate jobs is small and continuous. To give an impression of the grey area where higher education might be required but is not essential, we tested whether the occupation-specific HERI is significantly above the cut-point, and indicate which occupations fall in a grey area where the difference is not significant.

11. See note 2.

12. See note 2.

5. Validation

Is ISCO(HE) 2008 a valid indicator of graduate jobs? While its face validity is assured, in that it is based on the use of high skills, its operationalisation using the Survey of Adult Skills (PIAAC) data needs assessment.

We investigate in two ways. First, in this section we ask whether the outcome is distributed plausibly (that is, as expected) across major occupational groups. We also examine whether the implied relative quality of graduate labour varies across countries in ways that are consistent with the Survey of Adult Skills' (PIAAC) objective indicators of relative quality, measure by the literacy and numeracy of the country's graduates and other workers. Second, in the next sub-section we investigate how well the indicator predicts expected outcomes for individuals.

The aggregate distribution of graduate jobs across occupations, and the implied distribution of graduate labour quality

Does the overall spread of graduate occupations among major groups appear *prima facie* plausible? The classification broadly confirms ISCO's mapping of higher education to the first two major groups, but also suggests that the definition is too rigid at least for some countries where occupations outside of this narrow group require higher education (see Figure 1). Specifically, 90% of the minor groups in major group 1 and 93% in major group 2 are classified as graduate-level jobs across countries. However, in contrast to ISCO, about 43% of the minor groups in major group 3 are also graduate jobs. Further, there is a small but non-negligible proportion of graduate-level occupations in major groups 4 "clerical support workers". Thus, in at least some countries employers require graduates to do these jobs competently.

The distribution of graduate and non-graduate occupations in ISCO(HE) 2008 varies across countries, as allowed for in the classification procedure. Taking, first, managers, the classification of jobs within this major group is largely stable across countries. For example, Managing directors and chief executives or business services and administration managers are graduate jobs everywhere. But there is variation with respect to sub-major group 14 "Hospitality, Retail and Other Services Managers". Hotel and restaurant managers are classed as graduate jobs in some countries, for example Poland, but not in others, for example the United Kingdom. Variations within major group 2 appear to stem on one hand from differences in training requirements for nurses and primary school teachers and on the other from different qualification demands to perform jobs as "Creative and performing artists".[13] Overall, the country differences are most pronounced in major group 3. None of the included minor groups requires a university degree in every country, but every occupation is appropriate for graduates in at least one country. Occupations such as "331 Financial and mathematical associate professionals", "333 Business services agents", "335 Regulatory government associate professionals" or "351 Information and communications technology operations and user support technicians" are graduate jobs in the majority of countries: this observation alone illustrates the significant error that can be made by treating managers and professional as the only graduate jobs. By contrast, "312 Mining, manufacturing and construction supervisors", "313 Process control technicians" or "342 Sports and fitness workers" are classified as graduate jobs in only a few cases. Overall, at least some of the "Technicians and Associate Professionals" occupations are graduate jobs in every country.

13. There is the risk that the variation in graduate occupations among Health Professionals is partly the result of our imputation procedure. The low frequency minor groups "223 Traditional and complementary medicine professionals", "224 Paramedical practitioners" and "225 Veterinarians" receive the average HERI value from the corresponding sub-major group, which is dominated by the large minor-groups "222 Nursing and midwifery professionals" and "226 Other health professionals". This constellation is specific to Health Professionals.

While the coefficients in the first step can vary between countries, the threshold between graduate and non-graduate job is identical across countries. The rationale is that once the relative quality of graduates is taken into account, graduate jobs should map to the same levels of higher education requirements. We have hypothesised that the differences in the distribution of graduate jobs over and above job skills reflect perceived differences in the relative quality of graduates. Employers in a country with an excellent VET skills system are likely to be able to substitute workers with non-graduate qualifications satisfactorily to the same job that, in another country, might require graduate-level skills. In the following, we test this hypothesis using the skills proficiency information on literacy and numeracy skills in PIAAC.

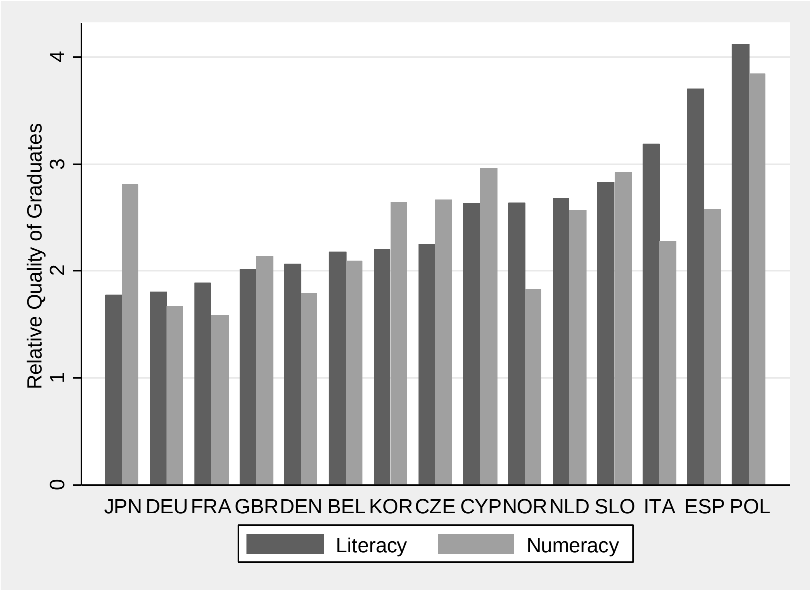
Based on the PIAAC skills data, the OECD distinguishes between five proficiency levels. At levels four and five, individuals are thought to be cable of integrating information from various sources, make complex inferences and evaluate models and concepts (OECD, 2013b). For each country, we calculate the proportion of graduates with skills at level four and above over the proportion of people at the same proficiency levels in the qualification group that is the closest feasible substitute to graduates.

Education and training system across OECD countries differ in the access to professional qualifications at post-secondary level or above (ISCED4B or ISCED5B) and the pathways from there into higher education. These specificities will shape individual educational choices. In effect, there are large differences in the uptake of non-academic post-secondary qualifications between countries. For example, less than 4% of the adult population in the Netherlands, 1% in Italy and virtually nobody in the Slovak Republic held a non-academic degree at post-secondary level or above in 2011. In contrast, more than 20% of the adult population in Japan, Denmark or Belgium (Flanders) graduated with a professional degree at post-secondary level or above. Thus, in the former group of countries, the closest feasible substitute to graduates from higher education are most likely those that finished upper secondary education, whereas in the remaining countries professional post-secondary education is likely to be the closest educational substitute.

Figure 2 depicts the objective relative quality of graduates in literacy and numeracy skills over their closest substitute between countries. The country rankings in the two skill domains are similar but not identical. The spearman rank correlation coefficient is 0.49. Overall, graduates were more likely to have high-skill levels, but the advantage varies. In terms of literacy, the relative quality of graduates was smallest in Japan, Germany and France and largest in Italy, Spain and Poland. With respect to numeracy skills, graduates in France, Germany and Denmark had the smallest relative advantage, whilst the gap was largest in the Slovak Republic, Cyprus[14] and Poland.

14. See note 2.

Figure 2. Relative quality of graduates over the closest educational group



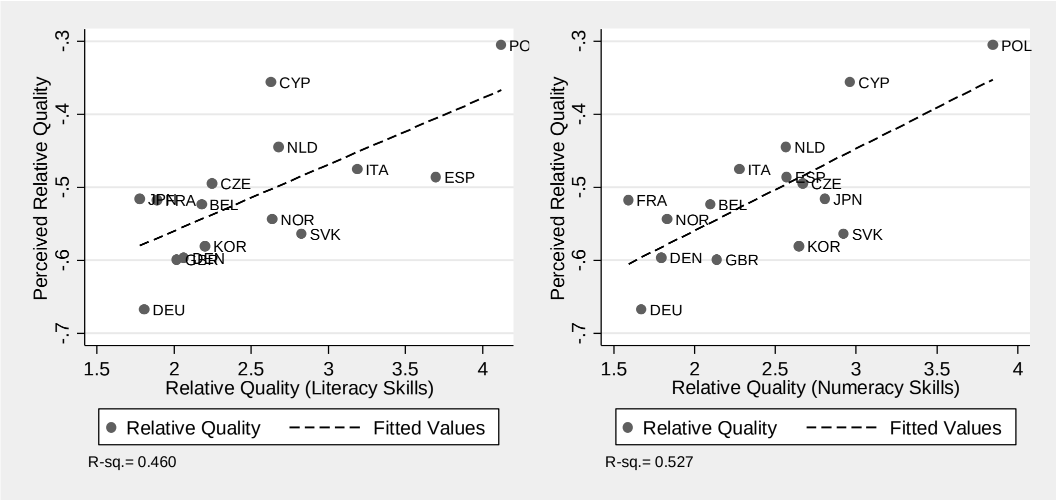
Notes: For Cyprus see note 2. Proportion of graduates at skills level 4 or above over the proportion of people at the same proficiency levels at ISCED3 (Italy, the Netherlands, the Slovak Republic) or ISCED4 and ISCED5B (remainder of the countries).

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Next, we correlate the objective relative quality of graduates with the estimated perceived quality displayed in Table 4. The scatterplots in Figure 3 reveal clearly positive associations between both measures of relative quality. Cross-national differences in the relative proficiency of graduates in literacy skills explain 46% of the variation in the estimated demand for graduate jobs over and above jobs skills. Relative differences in numeracy proficiency account for 52.7% of the variation in the dependent variable. Together both measures are jointly significant (p=0.004) and can explain 60.7% of the variation in the perceived quality of graduates (adjusted R-sq.=54.1%). Thus, variations in the prevalence of graduate jobs over and above job skills can be clearly attributed to differences in the relative quality of graduates. Still, some countries such as Cyprus[15] or the Slovak Republic are situated somewhat off the regression line. Other determinants such as regulations, attitudes towards higher education, systematic credentialism, or the relative wage of graduates might have an influence on the perceived relative quality beyond generic competencies.

15. See note 2.

Figure 3. Perceived and objective relative quality of graduates between countries



Note: For Cyprus see note 2.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

In all, HERI and resulting distribution of graduate jobs follows sensible patterns. Differences in the prevalence of graduate jobs can be attributed to variation in the relative quality of graduates, even if other factors, such as relative prices, may also play a role.

Outcomes for graduates

ISCO(HE) 2008 presents, as shown above, a *prima facie* plausible distribution of graduate jobs across major occupations, with few anomalies, and suggests that modern graduate jobs should be defined more broadly than is implied by the traditional definition.

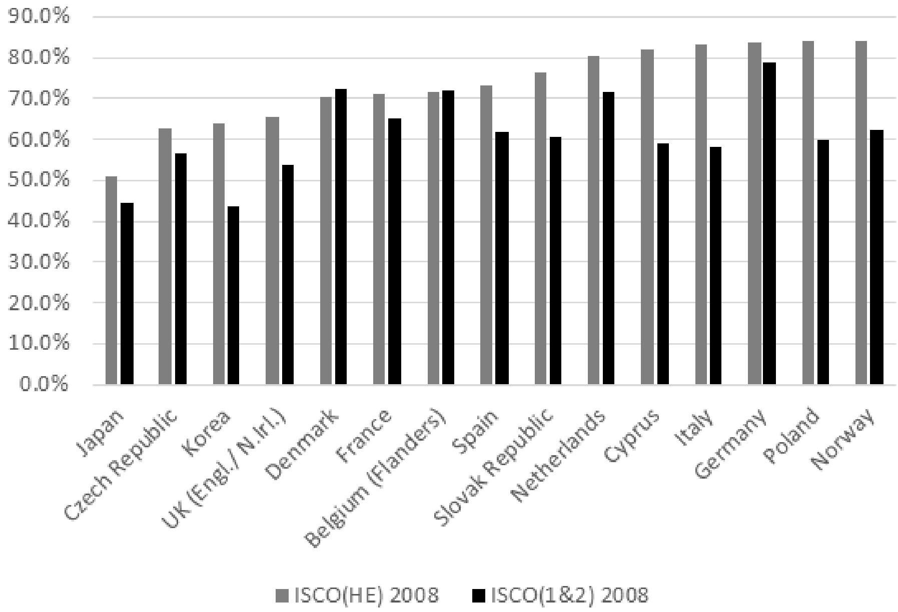
In this sub-section we examine the criterion validity of the indicator, by investigating the association of the indicator with expected outcomes. We analyse the deployment of graduates in graduate jobs in the employed labour force, and the connections between graduate job classification and three labour market outcomes: wages, job satisfaction, and training. We compare the performance of ISCO(HE) 2008 against traditional definitions, which we term ISCO(1&2) 2008 and ISCO(RM) 2008. The former classifies the first two major groups (except for sub-major group 14) as graduate jobs, and other groups as non-graduate, in every country. The latter is based on what graduates do; a minor group is deemed a graduate job if the majority of workers hold a degree from higher education. This corresponds to the often applied method of realised matches in the overqualification literature that has been advocated by (Verdugo and Verdugo, 1989) and is still applied to measure overqualification (e.g. Boll and Leppin, 2014). Minor groups are classified country-by-country.

Deployment of graduates and non-graduates

Do graduates get to work in graduate jobs? Even though matching of skilled workers to skilled jobs will be imperfect, one would expect a valid indicator of graduate jobs to reflect the matching process. Overall, we find that roughly 68.7% of graduates worked in a graduate job according to ISCO(HE) 2008, significantly above the 57.2% implied by ISCO(1&2) 2008. The flipside is that according to ISCO(HE) 2008 relatively more non-graduates worked in graduate positions than in ISCO(1&2) 2008. The proportion is small though; only about 14.2% of non-graduates were active in graduate jobs based on ISCO(HE) 2008. The figure of matched graduates puts our classification results in between the findings by (Croce and

Ghignoni, 2012) and the estimates based on REFLEX data (Verhaest and Van der Velden, 2013). The derived proportion of matched graduates for Britain is similar but not identical to earlier findings for all tertiary-level graduates (Green and Henseke, 2014).

Figure 4. Proportion of graduates in graduate jobs across countries/economies by classification



Notes: For Cyprus see note 2. Base: Employed labour force who had finished their initial cycle of education.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The proportion of matched graduates varies across countries (see Figure 4). In most countries more than 70% of graduates worked in graduate jobs. Japan, the Czech Republic, Korea and the United Kingdom are at the bottom, whereas Germany, Norway and Poland have the largest proportion of matched graduates according to ISCO(HE) 2008. The corresponding proportion of mismatched graduates are larger than the figures based on REFLEX data and the resulting country rankings are only loosely related. However, REFLEX measured the proportion of overqualification among a cohort of young graduates and not the whole graduate workforce. Interestingly, the gap in the proportion of matched graduates between ISCO(HE) 2008 and ISCO(1&2) 2008 varies considerably across countries. In Denmark, Belgium and Germany, our modern and the traditional classifier produce very similar proportions of graduates in graduate jobs, whilst there is a considerable gap between both figures in Korea, Italy, Cyprus,[16] Norway and Poland.

Labour market outcomes of matched and mismatched graduates

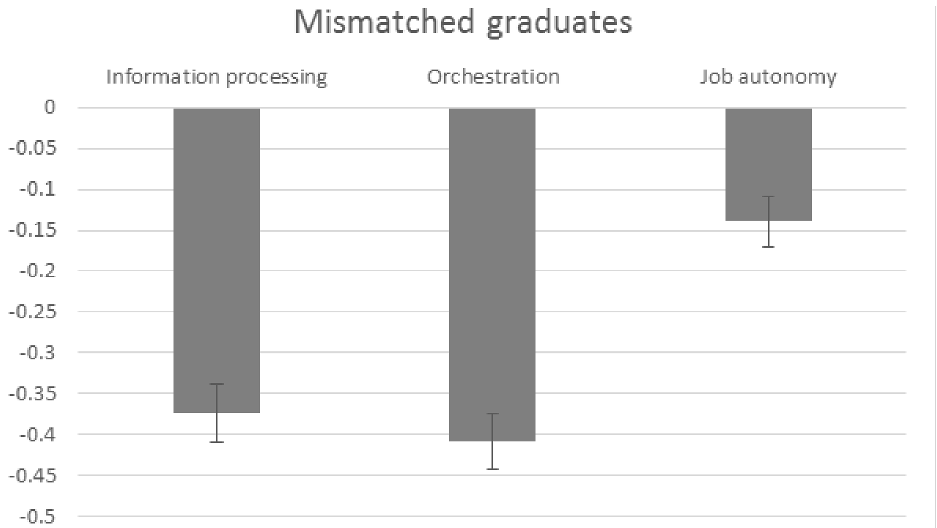
If ISCO(HE) generates a plausible picture of the deployment of graduates in graduate jobs, how well does it predict expected labour market outcomes? The better the classification, the more accurately it should predict these outcomes. Comparisons with the traditional classifier of graduate jobs (to be termed "ISCO(1&2)2008") based on ISCO major groups 1 and 2, and with a classification based on realised matches ("ISCO(RM)2008") can establish whether there is a gain in adopting ISCO(HE)2008 rather than these existing classifications.

16. See note 2.

First, it might be argued that occupations subsume multiple, not necessarily homogenous jobs, and that the job-holder determines the skills used, not the nature of the job. It is just conceivable that graduates in non-graduate occupations perform high-level jobs that are not properly captured by the occupational classification. To check this possibility, we compared skills use within skill-groups, according to whether they were in a graduate job or not. We ran linear regressions of the average over required information processing skills, the average orchestration skills and autonomy scales on a variable that distinguishes between matched and mismatched graduates, including also controls for gender, age, sector and country dummies. The sample is restricted to working age adults, who finished their initial cycle of education and worked in an occupation within what we have called the "risk zone", where the potential for misclassification is strongest, that is, in major occupational groups where occupations are likely not to fall all in one category (1, 2, 3, and 4). Matched graduates are the reference category. The skills use scale and the job autonomy scale are standardised for each country to mean zero and standard deviation of one.

Figure 5 depicts the results on the variable of interest. The estimation results confirm that there is heterogeneity in skill use by educational level and job type: mismatched graduates use significantly less skills at work and have lower job autonomy than matched graduates. The differences particularly in average job skills are sizeable and correspond to .35 to .4 standard deviations units.

Figure 5. Skill use on the job compared to matched graduates in the risk zone



Notes: The reference category is matched graduates (graduates working in graduate jobs defined by ISCO(HE) 2008. The sample is restricted to people who finished their initial cycle of education and work in "risk zone" occupations. Controls included for gender, age, sector and country.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Next we analyse how well ISOC(HE)2008 predicts individual labour market outcomes. We expect graduates in graduate jobs to earn higher wages, to have fewer reasons to be dissatisfied with their job, and to receive more training than graduates in non-graduate jobs. These outcomes are captured as follows:

- *Log Hourly Wages:* The natural logarithm of the hourly earnings including bonuses for wages and salary earners, converted to PPP-USD. Values in the 1% and 99% percentile have been removed to protect against potential distortions from outliers. Previous empirical evidence and theoretical arguments suggest that mismatched workers earn less than matched workers with the same level of education.

- *Low Job Satisfaction:* Question on job satisfaction with values ranging in five steps from 1 "Extremely satisfied" to 5 "Extremely dissatisfied". Low job satisfaction is defined as a binary variable that distinguishes satisfied (categories 1 and 2) from non-satisfied workers (responses 3, 4 and 5). Mismatched workers are more likely to express dissatisfaction with their job (Allen and Van der Velden, 2001; Cabral Vieira, 2005).

- *Long Training:* Binary variable that receive the value one if workers participated for more than five days in non-formal job-related training in the 12 months before the interview. A value of zero is assigned if workers had either participated in non-formal job-related training for five days and less or not at all in the last 12 months. The association between further training and mismatch status has seen much less scrutiny. But recent research suggests that further training is embedded into jobs and increases with skill use (Allen and de Grip, 2012; Mohr et al., 2015). As graduate jobs are more skill intensive, we expect matched graduates to engage more frequently in long training.

The top panel of Table 6 reports the results from linear regressions of the outcome variables on the set of covariates and the ISCO(HE)2008 classification of jobs for the total group of employed graduates. The bottom panel summarises the findings for graduates in the risk zone. We compare the results against the traditional classifier and the realised-matches classifier.

Table 6. Labour market outcomes of matched over mismatched graduates, by classification method

	Log hourly wages			Job dissatisfaction			Long non-formal training		
	ISCO (HE) 2008	ISCO (1&2) 2008	ISCO (RM) 2008	ISCO (HE) 2008	ISCO (1&2) 2008	ISCO (RM) 2008	ISCO (HE) 2008	ISCO (1&2) 2008	ISCO (RM) 2008
Total workforce									
Graduate Job	0.344 (0.0128)	0.301 (0.0110)	0.283 (0.0119)	-0.101 (0.0129)	-0.0985 (0.0108)	-0.0764 (0.0123)	0.0793 (0.0136)	0.0540 (0.0111)	0.0512 (0.0116)
N	12 073	12 073	12 073	15 330	15 330	15 330	14 471	14 471	14 471
R-sq	0.396	0.386	0.378	0.058	0.059	0.054	0.045	0.042	0.041
Risk zone: ISCO major groups 1, 2, 3, 4									
Graduate Job	0.263 (0.0148)	0.222 (0.0117)	0.199 (0.0124)	-0.0869 (0.0149)	-0.0835 (0.0121)	-0.0582 (0.0128)	0.0702 (0.0161)	0.0384 (0.0116)	0.0351 (0.0129)
N	10 799	10 799	10 799	13 597	13 597	13 597	12 797	12 797	12 797
R-sq	0.396	0.395	0.386	0.053	0.055	0.051	0.039	0.036	0.036

Notes: Results from linear regressions of the three outcomes (log hourly wage rate, job dissatisfaction and long job-related non-formal training) on the binary graduate job indicator, age, age squared, a gender dummy, set of dummies for public and not-for profit work organisations, a foreign-born dummy and a full set of country dummies. The sample is restricted to workers with completed higher education who finished their initial cycle of education.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The results confirm that working in graduate jobs is associated with a significant pay premium, a smaller probability to express dissatisfaction with the job, and a higher probability to engage in long job-related non-formal training. The findings hold both in the total sample as well as in what we have called the "risk zone". ISCO(HE)2008 outperforms ISCO(RM)2008 and performs better or at least as well as ISCO(1&2)2008. The absolute values of the estimated coefficients and figures for R squared are generally larger than for the other two classifications.

Further validation regressions (not shown here) in the sample of graduates working in jobs in major groups 3 or 4 confirm the superior performance of our modern classifier to explain the stylised facts of overqualification. Even in this contested group of occupations, graduates that work in graduate jobs according to ISCO(HE)2008 earned on average 18.9% more than mismatched graduates. If we had used the realised-matches classifier ISCO(RM) 2008 the estimated pay premium of matched graduates would have been 16.5%.

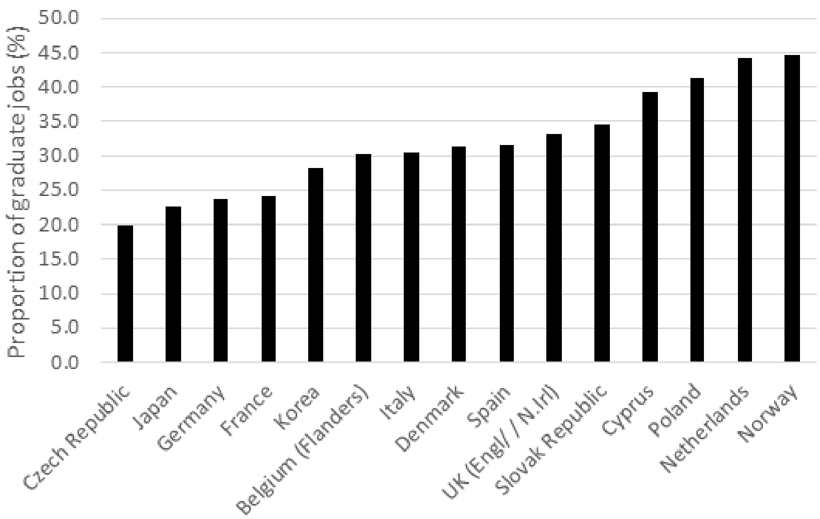
In all, the graduate jobs classifier ISCO(HE)2008 meets multiple validation criteria, and does so better than the realised-matches classifier ISCO(RM)2008 and better than or as well as traditional ISCO(1&2) 2008. Graduates in non-graduate jobs defined via ISCO(HE)2008 use lower skills at work, earn less, are more likely to be unsatisfied with their job and participate less in long training than matched graduates. The results hold in the total sample, the risk zone and a sample restricted to major groups 3 and 4. Differences in the prevalence of graduate jobs in the risk zone can be attributed to objective differences in the relative quality of graduates. Our approach is thus an improvement over existing practice. It is a data-driven, transparent and replicable indicator that is based on a theoretical concept of graduate jobs. It develops a more nuanced picture of graduate jobs for international comparison by taking country-specific features of the graduate labour market into account. By exploiting self-reported qualification requirements and the frequency of certain, well-defined tasks at work, we were able to test the proposed ISCO mapping of qualification levels to occupations across multiple countries. Our results suggest that the range of graduate jobs in ISCO is often too narrowly focused on traditional professional positions. In most countries, graduate jobs encompass a broader field of occupations.

6. The distribution of graduate jobs

Distribution across countries

As can be seen in Figure 6 and Table 7 (first column), the prevalence of graduate jobs varies considerably across countries, according to ISCO(HE)2008, consistent with the expectations discussed in section 2. There is a group of countries – consisting of the Czech Republic, Japan, Germany, and France – with a distinctly lower proportion of graduate jobs than the remaining countries. It is lowest in the Czech Republic, Japan, Germany and France (20-24%) and almost double that in Poland, the Netherlands and Norway (41-44%).

Figure 6. Proportion of graduate jobs in OECD countries/economies, 2011



Notes: For Cyprus see note 2. Base: Employed labour force who had finished their initial cycle of education.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

To some extent, this pattern of cross-country variation might reflect measurable structural factors that affect the demand for high-skilled labour, principally the different industrial compositions and the intensity of technological change as indicated by the intensity of R&D activities relative to gross value added. To capture these effects, we ran a saturated linear regression of our graduate job indicator on full sets of firm size, industry and sector dummies weighted by the provided sampling weights. The resulting gap between observed and predicted proportion of graduate jobs by country provides a measure of country-specific idiosyncrasies that might relate to underlying differences in the relative quality of graduates or production technology.

Using these findings, the second column of Table 7 shows the "surplus", that is, the extent to which in each country the prevalence of graduate jobs deviates from the predicted demand due to the industrial structure and firm-size distribution. The surplus varies between -7.7% (CZE) and 12.6% (POL). One can see for example that the Czech Republic or Germany have a relatively large negative surplus, implying that the low prevalence of graduate jobs has little to do with the industrial structure. The value range between the smallest and largest surplus is, at 20.3 percentage points, only around 4.5 percentage points below the range of observed proportions of graduate jobs across countries.

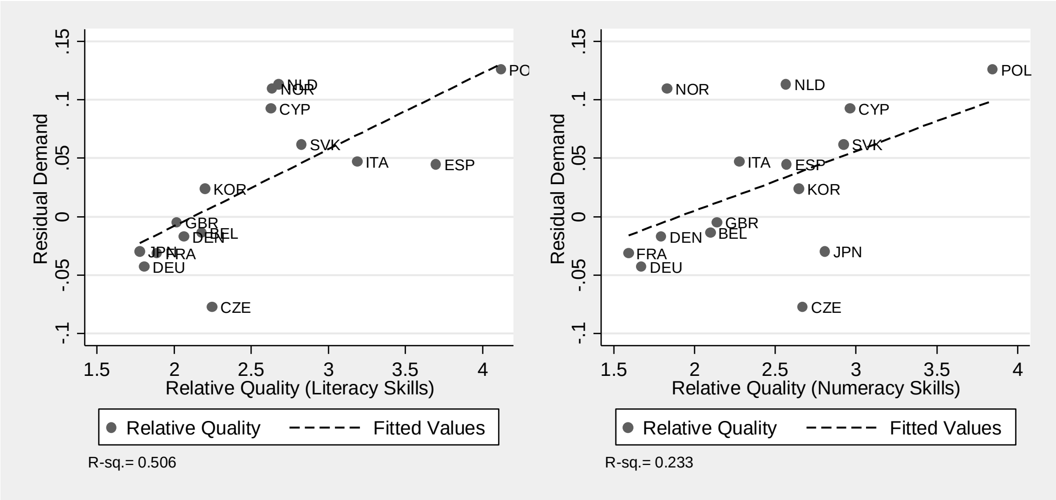
If it is not down to industry structure, to what extent can one account for the considerable cross-country differences in the use of graduate labour? As noted above, vocational and academic skills are, to a certain extent, substitutes (Card and Lemieux, 2001; Fitzenberger and Kohn, 2006). But, not only HE systems, also VET systems across the OECD vary hugely, with consequences for the relative quality of university graduates compared to the closest substitutable educational level (Eichhorst et al., 2015). Similarly, labour market norms and institutions affect the way skills are formed through work experience. Depending on the overall institutional design of the labour market and the education systems as well as the general expectation of the population, VET systems are associated with outcomes ranging from "dead-end track and second-choice education" (Eichhorst et al., 2015) to a valuable alternative to higher education.

Germany, in particular, is noted for its effective "dual" apprenticeship system, including high-level vocational skills for a sizable minority of the labour force; while Japan's internal labour markets are held to be efficient vehicles for in-work acquisition of high-level skills (Koike and Inoki, 1990). Such factors should be part of the explanation for why both Germany and Japan show low proportions of graduate jobs.

In fact, the differences in residual demand for graduate jobs correlate with the estimated perceived relative quality differentials across countries (see Table 4 for estimates of the perceived relative quality). The spearman rank correlation between residual demand and perceived quality is 0.51 and statistically significant at below the 10% level.

Figure 7 suggests further that not only the perceived quality but also the objective relative quality of graduates correlates with the residual demand. Both quality measures are jointly significant and account for 50.8 % (adj R-sq.=42.6%) of the variation in the residual demand for graduate jobs between countries. Thus, a clear fraction of the unexplained cross-national variation in the demand for graduate jobs is down to the relative position of graduates in the skills spectrum. In countries where graduates are the key source for high-level skills – Poland being a prime example – the relative quality of graduates relative to alternative labour is also high. Where the relative quality of graduates is low, however, as for example in Germany and France, graduate jobs are less numerous. Yet there are exceptions, such as Norway, where demand is high but relative quality low.

Figure 7. Association of the residual demand for graduate jobs and the relative quality of graduates



Note: For Cyprus see note 2.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

One might ask whether, in the face of the disruptions of the Great Recession and ongoing trends, this cross-national distribution of graduate jobs is changing over time. To study such change comprehensively will require repeated surveys of skill requirements. Nevertheless, structural change in the composition of occupations is likely to be a major source of change in the prevalence graduate jobs. In the short run one can usefully ask: how is the distribution of graduate jobs changing, conditional on no change in jobs classification.

The third column in Table 7 uses available information from the European Labour Force Survey (ELFS) to give a snapshot of change in the prevalence of graduate jobs. Owing to the adoption only in 2011 of the ISCO 2008 classification, the analysis is only available from that date, and applies only to European countries. The period 2011-13 was one of slow recovery from recession, and might be expected to signal a slow resurgence of lower-skilled jobs; while the long-term trend has been for growth in skilled jobs in most countries. In fact, expansion of high skills employment is not universal. As can be seen, rather than Germany or France catching up with the prevalence of graduate jobs elsewhere, both were falling further behind. Meanwhile, most of the high graduate job countries, with the exception of the Slovak Republic, exhibited increases.

Table 7. Proportion of graduate jobs by country/economy

Country/economy	Observed (%)	Surplus (%)	Change 2011-13
Czech Republic	19.8	-7.7	2.04**
Japan	22.6	-3.0	
Germany	23.8	-4.3	-1.81**
France	24.1	-3.1	-0.81**
Korea	28.2	2.4	
Italy	30.3	-1.4	1.81**
Spain	30.4	4.7	0.53**
Belgium	31.4	-1.7	1.32**
Denmark	31.6	4.5	0.46
UK (England / Northern Ireland)	33.2	-0.5	0.34
Slovak Republic	34.5	6.2	-1.99**
Cyprus*	39.3	9.2	0.31
Poland	41.3	12.6	
Netherlands	44.2	11.3	2.13**
Norway	44.7	10.9	1.49**
Average (weighted)	27.6		

Notes: * See note 2. “Observed” is the proportion of jobs that are graduate jobs [derived from the Survey of Adult Skills, (PIAAC); “Surplus” is the country-average residual from a saturated linear regression of graduate job status on fully interacted sets of industry dummies, sector dummies and workplace size dummies. “Change 2011-13” is the percentage change in the proportion of graduate jobs in the employed labour force, derived from the European Labour Force Survey between 2011 and 2013. ** p<0.05.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The variable role of R&D intensity in the demand for graduate skills

In addition to cross-country variation, the variation within countries can usefully be studied to examine the importance of technology. In particular, further insight into the distribution of graduate jobs can be obtained by investigating variations in the strength of its association with R&D intensity. If, as suggested above, the disposition of graduate jobs may reflect the relative quality of higher education and of vocational sources of high-skilled labour, so might also its relationship with R&D. As with the intercept term, the association between graduate jobs and R&D intensity is likely to be affected by the relative quality of ‘generalists’ university graduates over other types of qualification, such as VET.

To investigate this, we ran regressions allowing the R&D coefficient to vary across countries, and the key results are shown in Table 8 below. The findings re-confirm that, with the odd exception (Korea), graduate jobs are significantly more common in R&D intensive industries conditional on the other covariates. But, the estimated coefficients vary between 0.002 in Korea to 0.08 in Poland. In other words, industries with a one percentage point greater R&D intensity had between 0 and 8 percentage point larger probability to employ individuals in a graduate job. Notably, Germany and Japan, two countries with relatively good work-based systems for high-skill acquisition, also show a low coefficients linking R&D intensity with graduate jobs. At the other end of the scale, the largest coefficient is for Poland (0.08), which is further indicative evidence that the VET programmes in that country may be rather poor relative to the quality of its university programmes.

Table 8. The association of R&D intensity with the prevalence of graduate jobs within countries/economies

Country/economy	ISCO(HE) 2008		
	Coef.		S.E.
Belgium (Flanders)	0.025	***	0.004
Cyprus*	0.044	***	0.013
Czech Republic	0.047	***	0.01
Denmark	0.025	***	0.002
France	0.017	***	0.002
Germany	0.012	***	0.003
Italy	0.021	**	0.007
Japan	0.009	***	0.001
Korea	0.002		0.002
Netherlands	0.009	***	0.002
Norway	0.03	***	0.004
Poland	0.08	***	0.019
Slovak Republic	0.046	**	0.017
Spain	0.028	***	0.006
United Kingdom (England/ Northern Ireland)	0.03	***	0.005

Notes: * See note 2. Linear probability model of graduate job indicator on industry and country-specific R&D Intensities. Industry level variable are from 2010 (2009 for Japan). Parameters displayed are the country-specific coefficients of R&D intensity. A set of firm-size dummies, dummies for public and not-for-profit sector, a dummy for a non-service-sector-workplace, age and age squared, foreign-born, and a gender dummy are included as controls. Standard errors statistics are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

The remaining coefficients (not shown in the table) suggest further significant determinants of the graduate jobs demand besides R&D intensity. Workplaces in the public and charitable sector had a greater prevalence of graduate jobs than the private sector. Further, there appears to be significantly lower need for graduate jobs in non-service than in service industries. The prevalence of graduate jobs differed also by establishment size. Both ends of the spectrum (freelance job at the bottom end, and large workplaces with more than 250 employees at upper end) were more likely to require graduate jobs than small or medium-sized workplaces. Finally, there are socio-demographic differences: women and people born abroad were generally less likely to work in graduate jobs.

7. Conclusion

In this study we have derived a novel, data-driven and international indicator of graduate jobs, using a combination of self-reported required education, task data and further determinants of national demand for higher education in the labour market. The proposed procedure is transparent and replicable. It does not rely on expert judgement and is thus applicable to other countries and could track occupational upgrading wherever the required skills use data is available.

The resulting classifier ISCO(HE) 2008 is conceptually valid since it is grounded in the utilisation of high-level skills on the job. It takes potential cross-national differences arising from the varying relative quality of graduates into account, and the implied relative qualities are internationally correlated reasonably well with the relative proficiency scores of graduates and others. Further statistical tests show that the indicator explains the labour market outcomes of mismatched graduates – wage penalty, job dissatisfaction and lower participation in training – at least as well and usually better than the traditional delineation of graduate jobs as being drawn from occupations in ISCO 2008 major groups 1 and 2, and better also than an indicator based on realised matches within occupations.

The analyses based on ISCO(HE) 2008 show that graduate skills are essential in more than a narrow set of traditional professional and management jobs. Overall, 27.6% of jobs in the countries examined are graduate jobs, including many in ISCO major group 3. Yet there are considerable differences across countries:

- The proportion of graduate jobs in the labour market was lowest in the Czech Republic, Japan and highest in Poland, the Netherlands and Norway.

- Within countries technology intensity, establishment size and public ownership raise the proportion of graduate jobs, with the pattern largely consistent across countries. However, variation in industry structure and firm-size composition explains little of the differences between countries in the prevalence of graduate jobs.

- The demand does, however, reflect the country-level relative quality of HE, as opposed to non-HE routes to high-skill acquisition. The Survey of Adult Skills (PIAAC) data on literacy and numeracy proficiency of graduates and others corroborates this conjecture.

Potential caveats need to be noted. First, it is challenging to classify occupations and qualifications across countries into an internationally comparable taxonomy. Considerable efforts were made in PIAAC to ensure internationally commensurate classification, but some ambiguity remains. Second, our classification approach relies on the decomposition of the self-report qualification requirements into a component that can be attributed to the variation into more objective skill use indicators, further systematic determinants of HE demand, and an unobserved component that is assumed to summarise measurement and reporting error. In doing this, we assume that work tasks are exogenous to the individual worker, but this might not necessarily fully hold, especially for graduates who normally enjoy some autonomy over how they conduct their work. Third, a dichotomous classification system is likely to entail grey areas where the classification decision is close: Annex A lists those occupations in each country where the difference from the threshold is potentially within survey sampling error margins (there are not many of these). Moreover, the considerable simplification of a dichotomous graduate/non-graduate job classification is likely to be of value only in a meso- or macro-social context, and inevitably does not discriminate among heterogeneous graduate jobs.

With the above caveats in mind, potential uses of a graduate jobs indicator include application by HR professionals in careers guidance for HE students and graduates, and employability assessments of HE institutions (and sub-groups within them), in addition to its potential role in analysing high-skill labour markets. Such analyses can be conducted both between countries using The Survey of Adult Skills (PIAAC) and within countries using other data sets with decent sample sizes, wherever occupation has been appropriately coded.

To address further the functioning of graduate labour markets following the universal massification of higher education, the match between graduates and graduate jobs needs to be examined. A key feature of the graduate job concept behind ISCO(HE) 2008 is that it does not derive from job-holders' own qualification level. Consequently, among graduates the classifier allows us to define an overqualified or overeducated graduate as a graduate in a non-graduate job, without recourse to assumptions about how job skills are distributed within occupational groups. In forthcoming research, we utilise ISCO(HE) 2008 to analyse the international pattern of graduate overqualification.

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ANNEX A: LIST OF GRADUATE JOBS

This Annex lists occupation minor groups which are, at least in some countries, classified as graduate jobs. Shaded cells indicate that the skills requirements of the job are above or below the national threshold but the difference is not statistically significant at the 5% level.

Table A.1. Graduate jobs in major groups 1-4 (1 = graduate job, 0 = non-graduate job)

ISCO08 minor group	BE	CY[1.]	CZ	DE	DK	ES	FR	IT	JP	KO	NL	NO	PL	SK	UK
111 Legislators and senior officials	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
112 Managing directors and chief executives	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
121 Business services and administration managers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
122 Sales, marketing and development managers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
131 Production managers in agriculture, forestry and fisheries	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
132 Manufacturing, mining, construction, and distribution managers	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
133 Information and communications technology service managers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
134 Professional services managers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
141 Hotel and restaurant managers	1	1	0	0	0	0	0	1	1	0	0	0	1	0	0
142 Retail and wholesale trade managers	1	1	0	0	1	0	1	1	1	1	0	0	1	1	0
143 Other services managers	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1
211 Physical and earth science professionals	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
212 Mathematicians, actuaries and statisticians	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
213 Life science professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
214 Engineering professionals (excluding electrotechnology)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
215 Electrotechnology engineers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
216 Architects, planners, surveyors and designers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
221 Medical doctors	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table A.1. **Graduate jobs in major groups 1-4 (1 = graduate job, 0 = non-graduate job) (*continued*)**

ISCO08 minor group	BE	CY[1.]	CZ	DE	DK	ES	FR	IT	JP	KO	NL	NO	PL	SK	UK
222 Nursing and midwifery professionals	0	1	0	1	1	1	1	1	0	0	1	1	1	1	1
223 Traditional and complementary medicine professionals	0	1	0	1	1	1	1	1	0	1	1	1	1	1	1
224 Paramedical practitioners	0	1	0	1	1	1	1	1	0	1	0	1	1	1	1
225 Veterinarians	0	1	0	1	1	1	1	1	0	1	1	1	1	1	1
226 Other health professionals	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
231 University and higher education teachers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
232 Vocational education teachers	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1
233 Secondary education teachers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
234 Primary school and early childhood teachers	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1
235 Other teaching professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
241 Finance professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
242 Administration professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
243 Sales, marketing and public relations professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
251 Software and applications developers and analysts	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
252 Database and network professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
261 Legal professionals	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
262 Librarians, archivists and curators	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1
263 Social and religious professionals	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
264 Authors, journalists and linguists	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
265 Creative and performing artists	0	1	0	1	1	0	1	0	0	1	0	0	0	0	1
311 Physical and engineering science technicians	0	1	0	0	0	0	0	0	1	1	1	1	1	0	0
312 Mining, manufacturing and construction supervisors	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0
313 Process control technicians	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
314 Life science technicians and related associate professionals	0	1	0	0	1	0	1	0	1	0	1	1	1	0	1
315 Ship and aircraft controllers and technicians	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0
321 Medical and pharmaceutical technicians	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0
322 Nursing and midwifery associate professionals	0	1	0	0	0	0	1	1	0	0	0	1	1	0	1
323 Traditional and complementary medicine associate professionals	0	1	0	0	0	0	0	1	0	0	0	1	1	0	1

Table A.1. Graduate jobs in major groups 1-4 (1 = graduate job, 0 = non-graduate job) (*continued*)

ISCO08 minor group	BE	CY[1.]	CZ	DE	DK	ES	FR	IT	JP	KO	NL	NO	PL	SK	UK
324 Veterinary technicians and assistants	0	1	0	0	0	0	0	1	0	0	0	1	1	0	0
325 Other health associate professionals	0	1	1	0	0	0	0	1	0	0	0	1	1	0	1
331 Financial and mathematical associate professionals	1	1	0	0	0	1	1	1	1	1	1	1	1	0	1
332 Sales and purchasing agents and brokers	1	0	0	0	0	1	0	1	0	0	1	0	1	0	0
333 Business services agents	0	1	0	1	0	0	1	1	0	1	1	1	1	1	0
334 Administrative and specialised secretaries	0	1	0	1	1	1	0	1	0	1	0	0	1	1	0
335 Regulatory government associate professionals	0	1	0	1	1	1	0	0	1	1	1	0	1	1	1
341 Legal, social and religious associate professionals	0	1	0	0	0	1	0	1	0	1	0	1	1	0	0
342 Sports and fitness workers	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
343 Artistic, cultural and culinary associate professionals	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0
351 Information and communications technology operations and user support technicians	1	1	1	0	0	1	1	0	1	1	0	0	1	1	0
352 Telecommunications and broadcasting technicians	1	1	0	0	1	1	0	0	0	0	0	0	1	1	0
411 General office clerks	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
412 Secretaries (general)	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
413 Keyboard operators	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
421 Tellers, money collectors and related clerks	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0
422 Client information workers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
431 Numerical clerks	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
432 Material-recording and transport clerks	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
441 Other clerical support workers	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0

1. Note by Turkey:

The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union:

The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Source: OECD (2016), *Survey of Adult Skills (PIAAC)* (Database 2012), www.oecd.org/site/piaac/publicdataandanalysis.htm.

Analysing Adults' Skills: Proceedings of the 2nd International PIAAC Conference (Haarlem, 2015)

The OECD Survey of Adult Skills (PIAAC) assesses the proficiency of young people and adults in key information-processing skills essential for participating in the information-rich economies and societies of the 21st century. These are: literacy, numeracy, and problem solving in technology-rich environments.

This volume collects a selection of three papers from the 2nd PIAAC International Conference, jointly organised by the OECD and the Dutch Government in November 2015 in Haarlem, the Netherlands. Each of the papers represents an important contribution to the better understanding of issues of labour market and education policy that are at the centre of the policy concerns of many governments.

Contents

1. Ageing and Literacy Skills: Evidence from IALS, ALL and PIAAC. Garry Barrett and Craig Riddell.
2. Education, Labour Market Experience and Cognitive Skills: A First Approximation to the PIAAC Results. Juan Francisco Jimeno, Aitor Lacuesta, Marta Martinez-Matute and Ernesto Villanueva.
3. "Graduate Jobs" in OECD Countries: Analysis Using a New Indicator Based on High Skills Use. Golo Henseke and Francis Green.

Further reading

OECD (2016), *Skills Matter: Further Results from the Survey of Adult Skills*, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264258051-en

OECD (2016), *The Survey of Adult Skills: Reader's Companion, Second Edition*, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264258075-en

Write to us
Directorate for Education and Skills
OECD
2, rue André-Pascal
75775, Paris Cedex 16, France
edu.contact@oecd.org

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