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SKILLS BEYOND EDUCATION

An analysis of cognitive skill evolution and its implications for employment chances

Sara Flisi

Valentina Goglio

Elena Claudia Meroni

Esperanza Vera-Toscano

Catalin Dragomirescu-Gaina

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Unit DDG.01 – Econometrics and Applied Statistics

Contact information
Esperanza Vera-Toscano
Address: Joint Research Centre, Via Enrico Fermi 2749, TP 361, 21027 Ispra (VA), Italy
E-mail: esperanza.vera-toscano@jrc.ec.europa.eu
Tel.: +39 0332 78 5103
Fax: +39 0332 78 5733

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Executive Summary

Skills are at the core of improving individuals' employment outcomes and increasing countries productivity and growth while ensuring social cohesiveness. This is particularly relevant as today's global competition is characterized by a higher share of knowledge-based content which heavily relies on high-level cognitive and behavioral skills. The 1994-1998 International Adult Literacy Survey (IALS) and the 2012 Survey on Adult Skills (PIAAC) are unique datasets providing measures of individual cognitive skills for a representative sample of the adult age population across a number of OECD countries using methods of educational testing jointly with household survey techniques. Thus, they offer an exceptional opportunity to better understand how cognitive skills have evolved and how they are likely to influence our lives now and in the future, particularly in what refers to employment chances.

The aim of this technical report is threefold: (1) to analyse the current levels and distribution of skills in the working-age population of the sixteen Member States which participated in PIAAC; (2) to investigate to what extent these skills are important for labour market success; and (3) to examine how individuals (and the population) gain, lose and preserve their cognitive skills over time. To further complement this empirical evidence, we investigate the employment dynamics with respect to economic factors. The observed trends go in the direction of a concentration of employment in sectors which are more likely to require a higher educational level and consequently a higher level of skills. With all the caveats in mind, the reasoning behind this simple exercise is to grow awareness about the need to reinforce skills, and desirably, anticipate skills needs, through both efficient education policies and active labour market programs, including training.

The skills studied encompass literacy skills. The OECD (2013) argues that literacy, as a key information-processing competence, refers to the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential. Thus, there is growing recognition of its critical role for personal success workwise and beyond. Deeper knowledge on which literacy abilities to foster, at what age, and desirably through which interventions, is likely to have major implications for the design of effective policies aimed at improving employability and overall individual and social wellbeing. The main findings are reported below.

To begin with, average scores are useful to rank countries and to acknowledge which countries are top and worst performers. Nevertheless, **analysis of the distribution highlights how a consistent heterogeneity within the population can be found both in the countries which are outstanding performers and in others considered poor actors.** For example, looking at the quantiles can give us insight into the magnitude of country differences in averages, especially comparing top performing and low achieving countries. As an example, some countries may have higher averages than others, but lower values at top quantiles, resulting in a lower proportion of high achievers: It is the case of CZ and SK compare to DE, UK or AT. This type of analysis is particularly relevant for policy makers aiming at identifying particular groups upon which to intervene (e.g. low or high skill achievers).

Further, **although it is not possible to identify a proper casual impact, a positive association between education, skills and employment opportunities has been observed, suggesting that part of the positive effect of education may pass through the level of skills possessed by the individual.** This is an extremely interesting result. While the impact of formal education is stronger than that exerted by skills; we also observe that there are countries where the level of skills has the same –or higher- effect than a higher level of formal education (e.g. FI, SE and UK). Besides this level of skills is positively associated not only to employment opportunities, but also to the type of occupation in which individuals are employed. Thus, skills, and not only educational attainment are also crucial to represent the individual's level of competences and human capital.

Additionally, since empirical studies have shown that skills also evolve over time, the report investigates the skills dynamic disentangling ageing and cohort effects. **Our results support existing evidence on the general negative effect of age on the level of skills in all the European countries analyzed**. The age effect hits differently individuals according to their level of education or original level of skills; nevertheless, it comes out as a common feature for all countries studied. In an attempt to prevent skill loss, results further show that **general lifelong learning does not seem to contribute much to slowing down the deterioration on the level of skills**. The phenomenon of skill loss affects all countries, even those where adult participation in lifelong learning is widespread as DK, FI and NL. In contrast, the **cohort effect has a different impact across countries and educational levels**. Thus, some countries succeeded in keeping and even improving the skill level of younger cohorts (e.g. skill improvement for low-medium educated individuals in IT, IE, PL, FI or UK) compared to their older counterparts. However, in some other countries a serious deterioration in the level of skills of younger generations has been found (e.g. DK or SE for low educated people and UK or IE for highly educated individuals).

Lastly, given that labour supply is slow to adjust, and mostly in response to demographics and education policies, we find that labour demand can remain a source of policy uncertainty. Over the last decades, long-lasting **changes in labour demand have been brought about by several exogenous factors, on which policy makers have a limited control.** We suggest that **this source of uncertainty can be mitigated by a better understanding of the interactions between these *exogenous factors* and some key labour market institutional characteristics** that govern the functioning of different economic sectors. An informed policy maker, with a forward-looking perspective, might prefer to intervene along these dimensions in order to prevent potential labour market shortages/excesses and smooth the adjustment in labour supply.

Overall, this research work is intended to help policymakers, analysts, and researchers to establish effective and equitable arrangements, to ensure the creation of productive employment, and to promote sustainable growth. In terms of policy implications, two messages are worth noting. First, while it is highly recommended to invest in moving people from lower to higher educational levels, skills are at least as important in relation to generating positive social and economic outcomes. Learning the right skills today may improve employment status and social integration tomorrow, therefore efforts should be addressed in this direction. Second, the loss of skills between generations should be of special concerns among governments. If young generations perform worse than older ones it may result in a loss of competitiveness and well-being in broader terms for the whole society. This is particularly relevant if we consider that younger cohorts have to face a more competitive labour market requiring higher level of skills due to the higher proportion of automatized processes and the increasing technological complexity which involves all occupational sectors, including low skilled occupations. These results raise the flag for some structural changes which may have negatively influenced the process of skill acquisition by younger cohorts. Attention should seriously be paid to the evolution of the quality and efficacy of the different educational systems.

Introduction

In the current socio economic context, increasingly dominated by technological change and global competition and characterized by a higher share of knowledge-based content, human capital plays a crucial role, whose analysis requires a careful scrutiny of the distribution of knowledge and skills. In particular, adult skills are fundamental to ensure a successful integration of individuals in society (Sen, 1999). Poor skills prevent citizens from equally participating in the economic, social and political life of their countries, and expose them to worse employment opportunities, lower earnings and a much greater risk of economic disadvantage and overall social exclusion. An adequate investment in skills is critical to promote social mobility, thus tackling poverty, inequality and marginalization.

Until now, educational attainment has been the strongest and most widely used measure of human capital in the empirical literature about the socio economic outcomes of human capital. However, it is to some extent an indicator of what we know at the moment when we leave formal education. Human capital is more of a dynamic concept where individual skills play an important role. Skills are supposed to increase with working experience, as argued by the human capital theory (see Becker, 1976), but can also diminish if they are not used and with age; besides, the actual level of skills owned by individuals with the same educational level can vary across different age cohorts, due to changes in the educational system, in the structure and content of what is taught and how it is assessed. These are some of the reasons why the measurement of skills, rather than considering only the educational attainment, is considered a superior and more reliable approach to quantify human capital.

However, skills have been overlooked until relatively recently due to the impossibility of obtaining valid and reliable measurements of them across people. The 1994-1998 International Adult Literacy Survey (IALS) and the 2012 Survey on Adult Skills (PIAAC) are unique datasets providing measures of individual skills for a representative sample of adult age population across a number of OECD countries using methods of educational testing jointly with household survey techniques and individuals' demographic and socio-economic information. Thus, these surveys offer an exceptional opportunity to better understand how skills are likely to influence our lives, in particular, in what it relates to employment outcomes.

In particular, this report focuses on education, skills and employability. Among the different socio economic outcomes, employment is generally considered as essential for improving individual and social livelihoods and wellbeing shielding against poverty and socio-economic exclusion. Further, it provides stability and national economic development. Accordingly, this report aims to provide further empirical evidence on the following important questions:

1. What is the level and distribution of adult skills across EU countries?
2. Is there any relationship between skills and employability beyond formal educational attainment? If so, how does the level of skills influence individuals' likelihood of employment?

3. How do individuals (and the population) gain, lose and preserve their skills over time? And how can economic factors increase the demand for a given type of skills and decrease it for others?
4. More importantly, what role could or should government play in encouraging improvement of the skills of adults?

This report is structured as follows. Chapter 1 provides an overview of the two main surveys used in the analysis, namely IALS and PIAAC, and presents a summary description of the country-level distribution of skills. Chapter 2 investigates the relationship between formal education, skills and employability in the working age population. Using data from PIAAC (2012), standard multivariate methods are used to disentangle this relationship across 17 EU countries. Chapter 3 focuses on how and to what extent skills evolve over time, in an attempt to identify the main drivers of change in the skill composition within countries. Finally, since labour supply (individual skills) cannot be considered independently from labour demand, we also provide partial evidence of the evolution of the labour demand over the last two decades, showing how employment varied among economic sectors. The process of developing skills through education could benefit from being informed by the needs of the labour market. Governments should be proactive and coordinate their education and training policies with their economic and labour market policies for a better outcome. We devote Chapter 4 to provide further light on this important challenge. The final part of the report summarizes the main conclusions and policy implications.

Chapter 1. The distribution of skills in the 21st century[1]

In this chapter we present an overview of the distribution of skills in the European countries we consider in our analysis. Before doing so, we briefly describe the main datasets we will use in the study, namely IALS and PIAAC[2], and the implications in terms of comparability between the two surveys.

1.1. The international skills survey used in the analysis

1.1.1 The International Adult Literacy Survey (IALS)

The International Adult Literacy Survey (IALS) provided the world's first comparable estimates of the levels and distributions of cognitive foundation skills in the adult population. The IALS was the first attempt to establish a large scale survey on skills, which involved national governments, national statistical agencies, research institutions, the Organisation for Economic Co-operation and Development (OECD), co-ordinated by Statistics Canada and the Educational Testing Service of Princeton, New Jersey (USA).

Three separate data collections spanning a four years period were conducted in 24 countries or regions, and the survey was organized in two cycles (see Table 1). The first cycle included a first round of 9 countries surveyed in 1994, and a second round of 5 countries surveyed in 1996. The second cycle of the survey took place in 1998 and included 9 other countries.

[1] Chapters 1 to 3 were prepared by Sara Flisi, Valentina Goglio, Elena Claudia Meroni and Esperanza Vera-Toscano.

[2] Chapter 4 relies on the use of Eurostat data.

Table 1. Waves and countries participating in IALS

	YEAR		
	1994	1996	1998
COUNTRIES	Canada (English and French-speaking populations), France, Germany, Ireland, the Netherlands, Poland, Sweden, Switzerland (German and French-speaking regions), United States of America	Australia, Belgium (Flemish community), Great Britain, New Zealand Northern Ireland	Chile, the Czech Republic, Denmark, Finland, Hungary, Italy, Norway, Slovenia Italian-speaking region of Switzerland

The type of skills investigated is literacy skills, defined not simply as the ability of reading a written text but, put more in context, the ability of using the information for the basic functioning of individuals in the society. More precisely, literacy skill is defined as the ability of "using printed and written information to function in society, to achieve one's goals, and to develop one's knowledge and potential" (Statistics Canada, 2003, p.15). For this reason three domains of literacy are investigated:

a) *Prose literacy*: understanding and using information from written text of various nature (newspapers, fiction, poems);
b) *Document literacy*: understanding, locating and using information contained in various formats (job applications, payroll forms, transportation schedules, maps, tables, and graphics, …);
c) *Quantitative literacy*: the ability to apply arithmetic operations to numbers embedded in printed materials, such as balancing a check book, calculating a tip, completing an order form, or determining the amount of interest on a loan from an advertisement.

Literacy performances are measured on three separate scales (one per each of the abovementioned domains) and are recorded on a score scale which ranges from 0 to 500. Scores are then further grouped in five literacy levels (Level 1 from 0 to 225, level 2 from 226 to 275 and so on). See Table 2 below.

Table 2: Levels of literacy in IALS (Prose and Document)

Level	Score range
Level 1	0-225
Level 2	226-275
Level 3	276-325
Level 4	326-375
Level 5	376-500

The sample size per each country is shown in Table A1, and has been designed to be representative of their civilian, non-institutionalized population aged 16-65.

1.1.2 The Survey of Adult Skills (PIAAC)

The Survey of Adult Skills is an international survey conducted as part of the Programme for the International Assessment of Adult Competencies (PIAAC)[3]; run in 2011 and 2012, it measures key cognitive and workplace skills needed for individuals to participate in society and for economies to prosper. Using household's interviews, the survey assesses the skills of about 150,000 working age adults (16-65) surveyed in 24 countries. The survey is the outcome of collaboration among the participating countries, the OECD secretariat, the European Commission and an international consortium led by Educational Testing Service (ETS) (OECD, 2013).

PIAAC assessed three domains of cognitive skills, namely literacy, numeracy and problem solving in technology-rich environments (PSTRE). According to OECD (2012), literacy is defined in PIAAC as "understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential"; numeracy is defined as "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life", while PSTRE is "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks". The first wave of PIAAC problem-solving survey focused on the "abilities to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer networks."

The proficiency that respondents showed in the three indicated skills is measured on a scale from 0 to 500 points (proficiency scales), which is divided into proficiency levels (from below 1 to 5 for literacy and numeracy; from below 1 to 3 for problem solving). The proficiency levels describe the attributes of the tasks that adults with particular proficiency scores can typically successfully complete (see Chapter 21 in OECD, 2013 for further details) and are defined by distinct value ranges on the proficiency scales. Hence, using the proficiency levels, the skills of an individual or a group can also be described by the proficiency level at which the score points are located. According to OECD, the proficiency levels are not intended to describe standards in a sense of defining levels that are appropriate for specific purposes; however, some inferences about skills levels and e.g. job requirements should be possible. This leaves two main measures for reporting the levels of skills of the population: mean score points on the proficiency scale and the share of the population that performs on a certain proficiency level. Proficiency levels are shown in Table 3.

[3] For the sake of simplicity, in this report we will use the acronym PIAAC to refer to the survey.

Table 3: PIAAC proficiency levels

Level	Score range	
	Literacy and numeracy	Problem solving
Below Level 1	1-175	0-240
Level 1	176-225	241-290
Level 2	226-275	291-340
Level 3	276-325	341-500
Level 4	326-375	
Level 5	376-500	

Contextual questionnaires further collected a broad range of information, including not only educational attainment but also family background, linguistic background, outcome variables and how skills are used at work and in other contexts, such as the home and the community.

Table A2 reports the number of individuals participating in each country.

1.1.3 Comparability issues

As explained in Chapter 13 of OECD (2013), PIAAC was specifically designed to link to IALS in the domain of literacy, while the substitution of the assessment of quantitative literacy with numeracy[4] made it impossible to establish the same type of connection for this domain, since numeracy represents a much wider concept than the former. PSTRE constitutes a new domain, so no comparison is possible.

In the literacy domain, around 60% of the assessment items in PIAAC were drawn from IALS and ALL (OECD 2013, p. 14), so as to ensure the strong link between surveys[5]. However, in IALS literacy was assessed on two separate scales (prose and document literacy), while in PIAAC there is one single scale. As explained in the updated documentation for IALS, following PIAAC, the prose and document scales have been re-scaled and combined into one literacy scale; this new scale allows for carrying out of trend analysis with PIAAC. Practically speaking, this implies that in the newly released microdata for IALS, new plausible values for literacy are included that are comparable to those provided by PIAAC. Nonetheless, a couple of slight differences remain; first of all, PIAAC expanded the type of texts used in IALS for assessing literacy: in addition to the continuous (prose) and noncontinuous (document) texts used in IALS, PIAAC also includes electronic and combined texts; secondly, PIAAC includes a measure of reading component skills which was not included in IALS (OECD, 2013).

[4] This took place already in the Adult Literacy and Lifeskills Survey (ALL), carried out between 2003 and 2006, which is the second international adult skills survey implemented by OECD countries, after IALS and before PIAAC.

[5] This link in the literacy domain is therefore granted also for ALL; however, since this survey covers only two of the countries that participated in PIAAC, namely Italy and the Netherlands, we decided to rely on PIAAC and IALS only, in order to have a wider group of countries in the analysis.

Finally, also some of the background questions in PIAAC and IALS differ, since PIAAC focuses more on information about the use of skills in the workplace compared to IALS. However, in key areas (educational attainment and labour force status) the information in PIAAC and IALS is provided using comparable questions. In the PIAAC dataset, a number of 'trend' variables are included, that is, variables related to information that was collected also in IALS, and that are recoded to match the metric or coding schemes of IALS, in order to make them comparable across countries.

The countries that participated in both surveys and for which it is possible to study evolution of literacy skills over time are 11: Belgium (FL), Czech Republic, Denmark, Finland, Germany[6], Ireland, Italy, The Netherlands, Poland, Sweden, and United Kingdom. It should however be pointed out that while for IALS the UK includes the whole country (Great Britain + Northern Ireland), only England and Northern Ireland participated in PIAAC, so there is a discrepancy in the representation of the country in the two surveys.

1.2. The distribution of skills across and within countries: a look beyond the mean

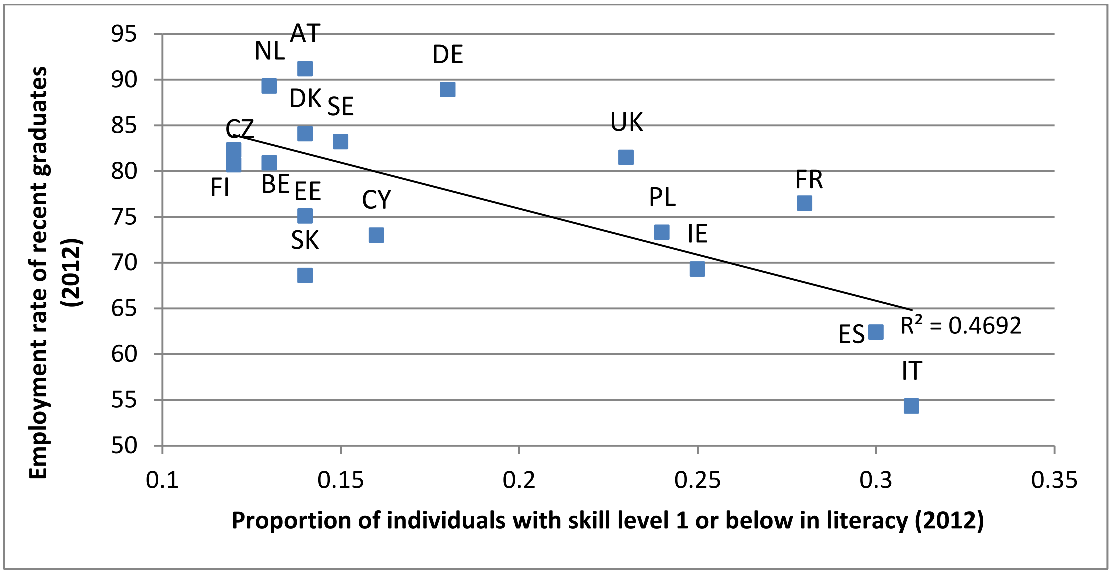
Skills have become a critically important "*tool*" of the current century. Proper skills are fundamental to achieving a more competitive economy and a more cohesive society, and the recent publication of the PIAAC Survey has generated large debates among academics and the general public on differences in performances between European countries. Countries like IT and ES, which are lagging behind in terms of economic performance and social cohesion, are also performing among the worst in terms of individual literacy and numeracy skills; on the contrary, countries like FI, the NL and BE (Flanders), with good economic and social indicators, rank among those with the highest individual average skills.

Analyses of the relationship between skills and economic and social outcomes are mostly limited to comparing average values among countries. However, despite having received less attention, just as important as the average levels of skills, is how these skills are distributed. If we take, for example, the lower end of the skill distribution (i.e. individuals who score at level 1 or below in literacy skills in PIAAC) and relate it to the benchmark of the strategic framework for European cooperation in education and training (ET 2020) concerning the employment rate of recent graduates[7] (as a possible proxy of economic performance), it appears that countries with fewer low-skilled adults tend to enjoy better economic performance (see Figure 1). Similar results are obtained if we compare the upper end of the skill distribution (i.e. individuals who score at level 3 or above in literacy skills in PIAAC) and a social outcome such as individuals' trust (see Figure 2): countries with higher shares of high-skilled individuals rank higher in levels of social trust.

[6] In PIAAC Germany does not include age as a continuous variable, which forced us to exclude the country from part of the analysis, as will be explained in Chapter 3.

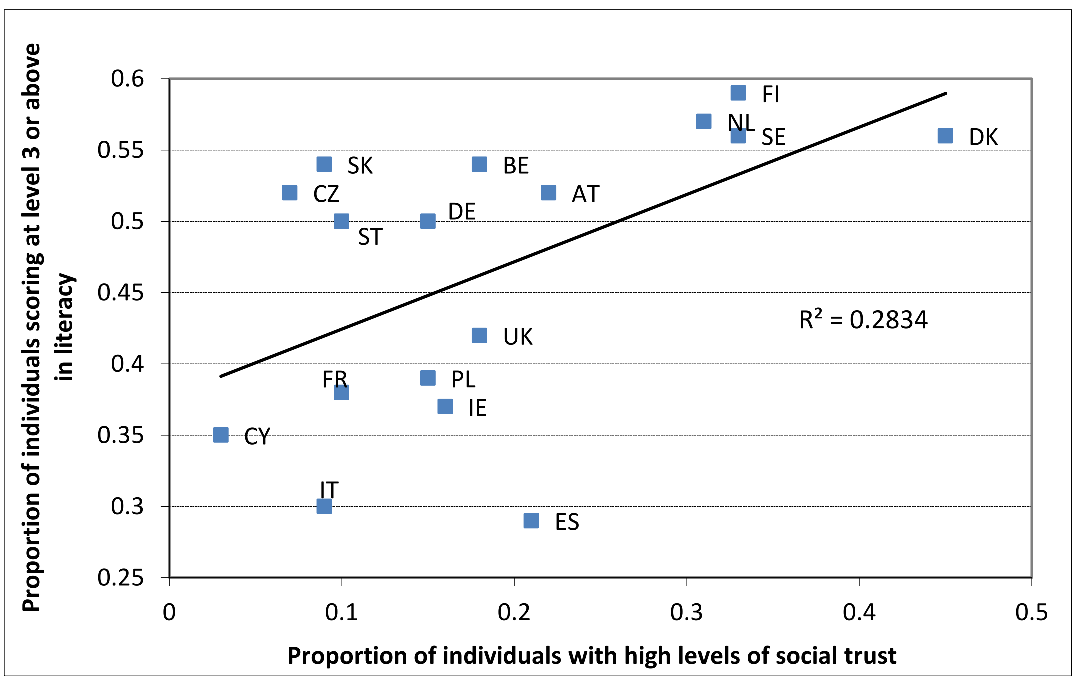
[7] This benchmark aims to employ 82% of 20-34 year old graduates from upper secondary to tertiary education having left education and training no more than three years before the reference year.

Figure 1. Relationship between the proportion of individuals with skill level 1 or below in literacy and the ET 2020 benchmark on the employment of recent graduates



Note: Own elaborations on PIAAC and Eurostat data.

Figure 2. Relationship between the proportion of individuals scoring at level 3 or above in literacy and individuals' social trust



Note: Own elaborations on PIAAC 2012 data. In PIAAC, the item on trust asks the respondents how much they agree – on a scale from 1 to 5, where 1 is "strongly agree" and 5 is "strongly disagree" – with the statement "There are only a few people you can trust completely". Individuals with a high level of social trust are defined as those who answered "disagree" or "strongly disagree" to the question.

These figures suggest that in evaluating the performance in terms of skills of a country, it can be relevant to go beyond the simple average scores, and analyse the distribution of skills. From a policy perspective, this is particularly important, since it can provide useful insight for a more targeted approach, assessing the efficiency of the system in providing the appropriate level of skills to all individuals, but also informing governments on the segment of the population where they should invest in order to achieve greater economic and social results.

As a first step in the analysis, we start by simply looking at the average score in numeracy and literacy and the standard deviation of the two scores in the surveyed countries, as a measure of how dispersed the skills distribution is. Figures are reported in Table 4.

Table 4. Mean, standard deviation and skewness for literacy and numeracy skills by country

Country	Literacy			Numeracy		
	Mean	Standard deviation	Skewness	Mean	Standard deviation	Skewness
Austria	269.45	43.96	-0.450	275.04	49.29	-0.536
Belgium	275.48	47.08	-0.517	280.39	50.59	-0.451
Cyprus	268.84	40.27	-0.357	264.63	46.84	-0.486
Czech Republic	274.01	40.79	-0.298	275.73	43.72	-0.260
Denmark	270.79	47.72	-0.735	278.28	51.23	-0.571
Estonia	275.88	44.40	-0.375	273.12	45.54	-0.362
Finland	287.55	50.67	-0.672	282.23	52.21	-0.594
France	262.14	49.02	-0.497	254.19	56.17	-0.485
Germany	269.81	47.40	-0.384	271.73	53.07	-0.474
Ireland	266.54	47.19	-0.554	255.59	53.66	-0.605
Italy	250.48	44.69	-0.274	247.13	49.99	-0.304
Netherlands	284.01	48.39	-0.558	280.35	51.07	-0.638
Poland	266.90	47.98	-0.322	259.77	50.72	-0.354
Slovak Republic	273.85	40.07	-0.616	275.81	47.60	-0.571
Spain	251.79	49.03	-0.424	245.82	51.32	-0.526
Sweden	279.23	50.56	-0.785	279.05	54.87	-0.690
United Kingdom	272.46	48.97	-0.431	261.73	54.88	-0.393

Note: Own elaboration on PIAAC data.

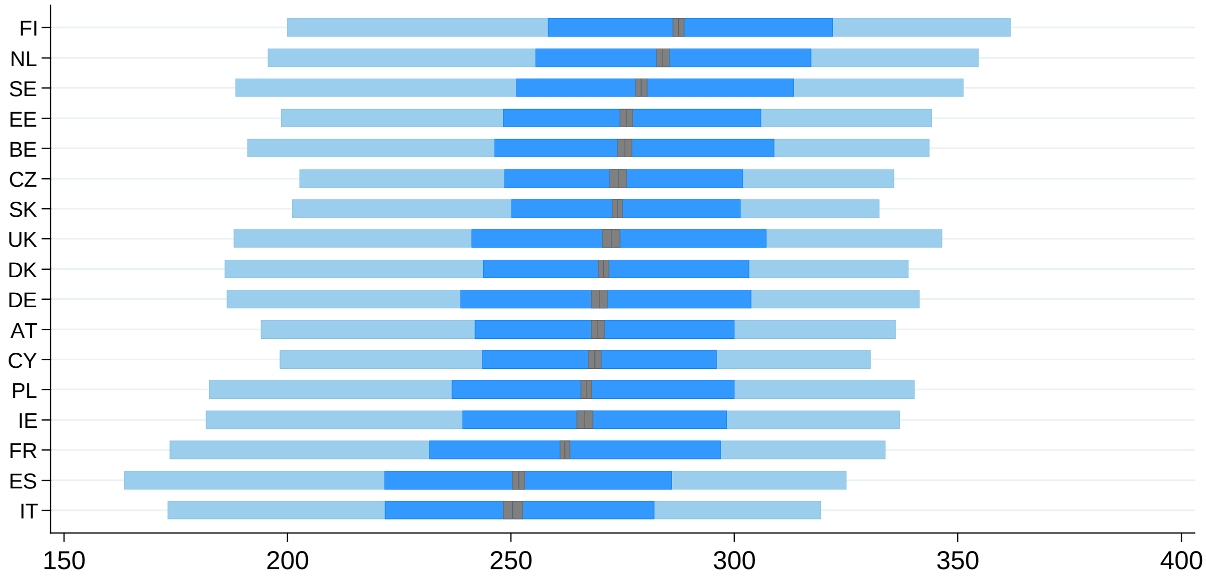
Average scores are useful to rank countries and to acknowledge which countries are – on average – top and worst performers. As widely known, we have IT and ES being the worst performers and FI, SE, NL and BE being the top ones. Nevertheless, looking at the standard deviation can provide some additional information. In particular, we see that for literacy three of the top performers have the higher standard deviation: SE, FI and NL have the most disperse distribution, together with ES and FR, which are, on the other side, two of the worst performers. If we consider numeracy, the situation changes slightly, with FI and SE having higher standard deviation, but also FR, DE, IE and the UK. This result highlights how a consistent heterogeneity within the population can be found both in countries that are outstanding performers and in others that are considered as poor performers. Countries performing in the middle are also less disperse. In particular AT, CY, CZ and SK show the lowest variance.

Higher dispersion means that the difference between the top and the bottom part of the distribution of skills is more pronounced. In Figure 3 and Figure 4 we report, for literacy and numeracy respectively, the mean skill level in the population (together with the 0.95 confidence interval, represented by the grey bars), the 25th and 75th percentiles (dark blue bars), and the 5th and 95th percentiles (light blue bars). In the figures we see that for example, although the Finnish are on average performing better than all the remaining countries in literacy, the bottom 5% of Finnish people are performing worse than their Czech or Slovak counterparts. On the other side, while on average CZ and SK perform better than many countries, we notice that the top 75% of the German, English, and Danish population performs better than the corresponding Czech and Slovak population. This suggests that a higher average performance does not necessarily imply a higher score at all points of the skills distribution, and therefore also that higher mean scores do not guarantee a higher proportion of high achievers. As a matter of fact, while CZ and SK have higher average performances, DE, DK and UK have a higher proportion of high achievers (here considered as those individuals scoring at proficiency level 4 and above), as can be seen in Table 5, where the distribution of the population by literacy skill level is reported. The same is true for FR and CY: the former has a lower average than the latter, but has a higher value of the 95th percentile, resulting in a higher percentage of individuals scoring at level 4 and above in FR than in CY.

Similar situations are observed for numeracy skills between SK on one hand, and AT and DE on the other: while SK has a higher average score, AT and DE display higher scores at the 75th percentile, and a higher share of population at skill level 4 or above.

Figure 3. Distribution of skills – Literacy

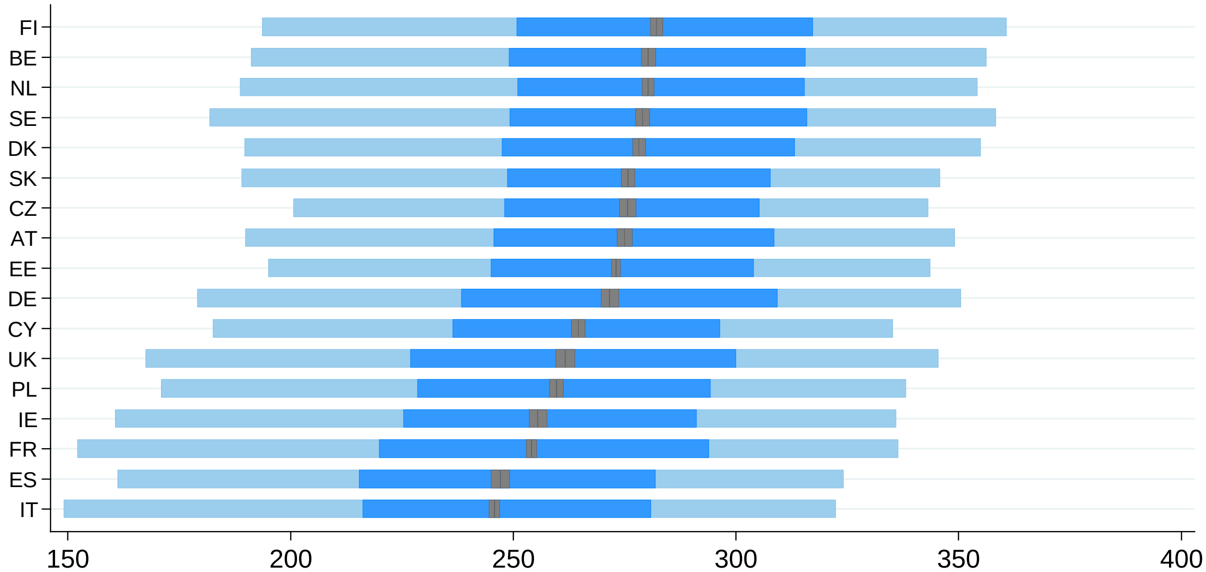
Percentiles in literacy proficiency: mean score and 0.95 confidence interval (grey bars), 25th and 75th (dark blue) and 5th and 95th (light blue)



Note: Own elaborations on PIAAC data.

Figure 4. Distribution of skills – Numeracy

Percentiles in numeracy proficiency: mean score and 0.95 confidence interval (grey bars), 25th and 75th (dark blue) and 5th and 95th (light blue)



Note: Own elaborations on PIAAC data.

Table 5. Distribution of the population by PIAAC skills proficiency level

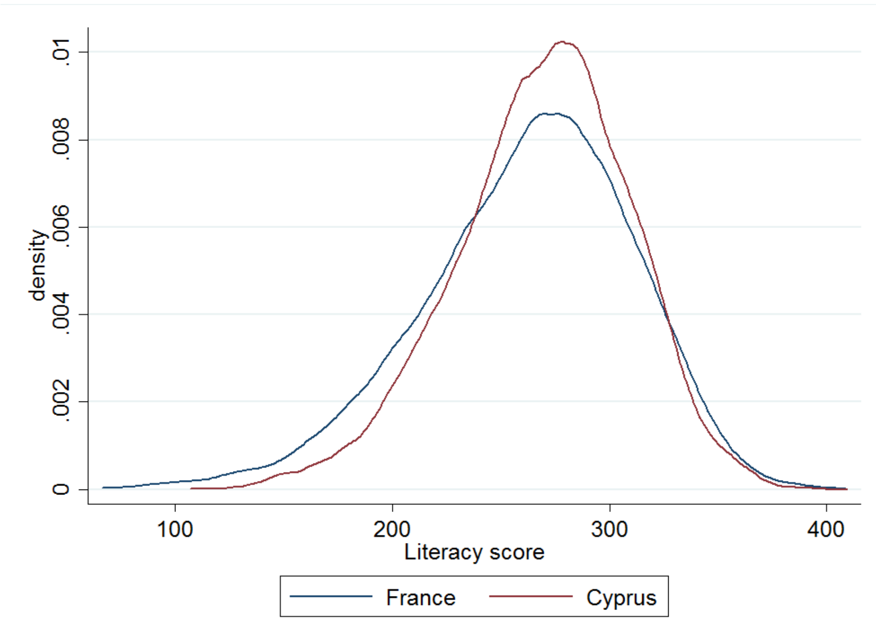
Country	Literacy				Numeracy			
	Level 1 and below	Level 2	Level 3	Level 4 and 5	Level 1 and below	Level 2	Level 3	Level 4 and 5
Austria	14.66	36.64	38.20	8.68	13.73	32.44	37.93	14.07
Belgium	13.46	28.83	39.17	13.39	12.92	27.55	36.19	18.19
Cyprus	11.69	31.95	33.10	5.58	15.96	31.02	28.79	6.54
Czech Republic	11.48	34.66	43.53	9.70	12.38	35.36	39.75	11.90
Denmark	15.32	34.14	39.63	10.53	14.30	29.71	38.61	17.00
Estonia	12.54	33.92	40.90	12.27	13.99	35.96	38.41	11.25
Finland	10.20	25.80	41.08	22.92	12.08	29.19	38.70	20.04
France	20.57	36.28	33.96	8.35	27.75	33.32	29.44	8.64
Germany	17.13	32.74	37.70	10.95	17.59	30.44	35.58	14.92
Ireland	17.03	36.27	37.15	9.08	25.03	37.90	28.83	7.77
Italy	25.77	42.63	27.23	3.71	30.87	38.80	24.71	4.97
Netherlands	11.44	26.47	40.75	19.08	13.18	27.93	38.86	17.77
Poland	18.57	36.04	35.04	10.35	23.56	37.28	30.29	8.87
Slovak Republic	11.46	34.89	45.34	8.04	13.56	32.29	40.97	12.91
Spain	26.87	39.20	28.08	5.09	30.27	39.47	25.38	4.12
Sweden	13.23	28.91	41.27	16.60	14.88	29.50	36.34	19.28
United Kingdom	15.15	33.08	37.12	13.24	22.50	34.44	29.02	12.63

Note: Own elaboration on PIAAC data. Reported skill levels correspond to PIAAC proficiency levels.

In Table 4 we also report the skewness of the two distributions for each country. Skewness quantifies how symmetrical a distribution is; a negative skewness means that the distribution is not symmetric and has a longer tail to the left, a positive skewness means that the distribution is again not symmetric, but with a longer tail to the right. For both literacy and numeracy, in all the countries we observe a negative skewness. While it is true that none of the skewness reported are substantial (they are all smaller than -1 – in absolute value), we can still notice some differences by country. In particular for literacy the higher skewness is observed in DK, FI and SE, and the lower in IT, CZ and PL; while for numeracy higher values are in NL, SE and IE and lower values still in IT, CZ and PL. In countries with higher negative skewness the distribution is shifted to the right, and the difference between the values at the lower end of the left tail and the mean is higher than the difference between the values at the upper end of the right tail and the mean, suggesting ah higher dispersion existing between the individuals with lower skills, rather than among the ones with higher skills. This finding confirms the discussion provided above about the distribution of skills presented in Figure 3 and Figure 4.

Overall, this exercise suggests that looking at the mean performance may not be enough, especially if policy makers aim at identifying particular groups upon which to intervene. So, taking one of the examples mentioned above as a case study, we could say that in CY literacy skills of the population are less dispersed than in other countries, and that on average the population performs in line with other countries. However, in order to improve average performance, CY should make an effort to increase the proportion of high scorers, focusing on the top part of the skill distribution. On the other side, FR, which is among the worst performers on average, has a higher proportion of individuals scoring at level 4 and above, comparable to the ones of SK and close to DE and DK, but at the same time it has a very large proportion of individuals scoring at level 1 or below. Thus, in FR the focus should be on low scorers, the ones at the bottom part of the skill distribution (see Figure 5 for the density distribution plot).

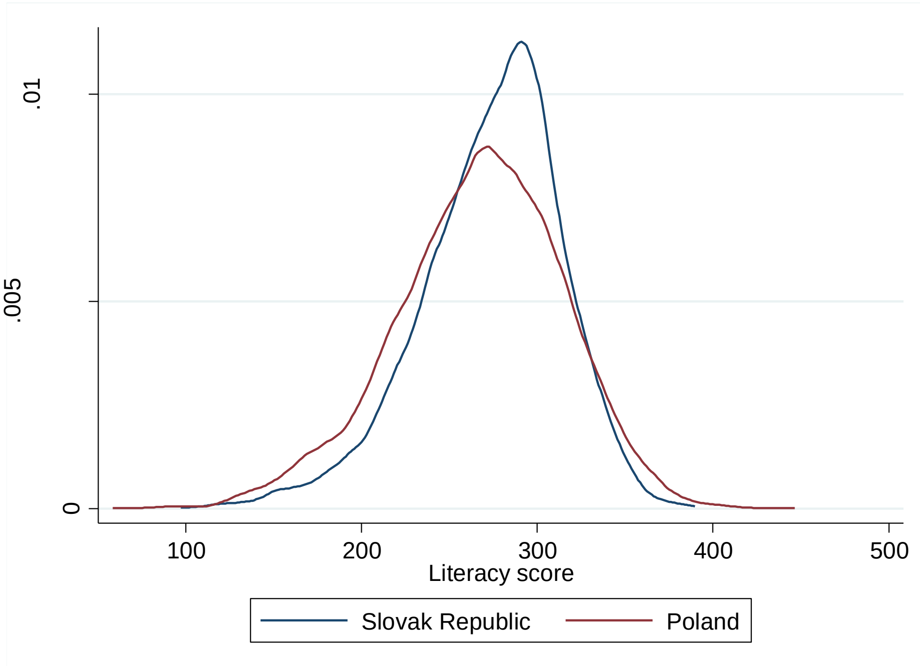
Figure 5. Density distribution in France and Cyprus, literacy score



Note: Own elaborations on PIAAC data.

Another example that shows how relevant it is to go beyond the mean and look at the whole distribution is shown in Figure 6. Slovakia presents a slightly higher average literacy score than Poland, but the distribution in the population is completely different, with the former having a much higher concentration of individuals close to the mean. On the contrary, Poland has a more dispersed distribution, with a higher incidence of both low and high scorers than Slovakia. Therefore, it appears that in Slovakia the need to invest in the lower end of the distribution is lower than in Poland.

Figure 6. Density distribution in Slovak Republic and Poland, literacy score



Finally, focusing on percentiles other than the mean is helpful for interpreting differences between countries and for having a sense of the magnitude of these differences. So, in Figure 3 and Figure 4 we notice for example that on average the Finnish perform better than the Spanish and the Italian, but "how much better" can be seen noticing that the average Italian score is as low as the score of the bottom 25% of the Finnish population, or that the average Finnish score is as high as the score of the top 75% of the Italian population.

These first descriptive analyses have pointed out some facts:

- First, countries differ not only in their average performance, but also in the distribution of skills within the population, and in particular in the degree of dispersion of the distribution itself;
- Second, differences in averages are not always reflected in differences at the top or bottom quantiles of the skill distribution: as an example, some countries may have higher averages than others, but lower values at top quantiles, likely resulting in a lower proportion of high achievers;
- Third, looking at the quantiles can give us insight into the magnitude of country differences in averages, especially comparing top performing and low achieving countries.

After this first overview of the level of skills and their distribution in the countries, we now move on to the core of our analysis. In the rest of the report, for the sake of simplicity we will rely for our study on one type of skill only, instead of some combination of the three available in the survey (literacy, numeracy and problem solving in technology-rich environments). Considering the very high correlation between the three skills (around 90% in PIAAC data), we think this is a reasonable simplification for the analysis. We disregarded problem solving from the possible choices because this would significantly reduce the sample we could use; first of all, a few countries (namely Cyprus, France, Italy, and Spain) did not participate in the Problem Solving test altogether; secondly, the test was administered only to people with some computer experience, which is not a representative sample of the population. We choose to consider literacy over numeracy for a few different reasons. Literacy skills are essential for the integration of the individual not only from an economic perspective, but also from a social standpoint, providing him/her with the basic skills for being an active citizen in the social and political domains as well (Sen 2000; Green and Riddell 2013). Moreover, from a purely methodological point of view, literacy skills are the only ones upon which a comparison between IALS and PIAAC can be built; as a consequence, the choice of relying on literacy rather than numeracy assures a higher level of coherence throughout the report.

Chapter 2. Skills as a determinant of employment

2.1. Introduction

The purpose of this chapter is to provide empirical evidence on the association between formal education, skills and employability among the working age population. The availability in the PIAAC dataset of information on both educational attainment and directly observed skills allows us to disentangle the separate effect of these two factors on the chances of labour market success. The chapter is organized as follows. The next section provides a brief literature review of the existing empirical evidence – as well as its theoretical framework – on the linkages between human capital and employment. This section provides a useful background for the empirical approach adopted in this report. Section 3 describes the details of the quantitative analyses developed in the chapter and presents some descriptive statistics on the variables used in the analysis. Empirical results are provided in Section 4, and Section 5 concludes.

2.2. Determinants of employment: The relevance of individuals' skills

The purpose of this section is to summarize the theoretical and empirical literature on the determinants of employment, paying particular attention to the relevance of individual skills.

The literature identifies, overall, three major factors related to **labour supply** that affect the likelihood of employment of any working age individual, namely: (a) his/her own human capital; (b) socio-demographic characteristics relevant to employment such as ethnic group or gender, but also immigration status; and (c) the willingness and ability of the individual to seek employment given alternative sources of income, physical disability, the need to care for children at home, etc., all of which affect labour force participation rates and thus employment. [8]

2.2.1. Human capital as a core determinant of employment

Human capital is a major predictor of employment outcomes, but it is also a very difficult concept to measure. As stated by Haveman, Bershadker and Schwabish (2003), human capital is the value that a given individual can add to any productive activity. Thus, researchers describe it as a function of a number of characteristics, such as educational attainment; work experience; job training; "soft skills" such as motivation or attitude, public speaking ability, creativity or the ability to work well with others; and skills themselves (e.g. strength or writing ability). However, due to the impossibility of obtaining

[8] In addition, labour demand factors - the characteristics of the regional labour market and the particular kind of worker skills required in the occupational sector for which he/she has skills – will also affect the likelihood of employment. This approach is out of the scope of the analysis in this technical report, but a preliminary exploration of the issue is provided in Chapter 4 .

valid reliable measurements of the many different aspects of human capital across individuals, **education attainment** and **experience** (often proxied by age) have largely been used as the two most common measures of human capital.

Thus, educational attainment is the strongest and most widely used measure of human capital in the empirical literature, and, not surprisingly, it is a major determinant of future employment (Card 1999). This is also consistent with the review by Wolman et al. (2008) who find that economic growth is largely driven by education levels of the workforce.

There are several theories linking higher levels of education with better employment opportunities[9]. For the purpose of our work we briefly introduce here two among the most relevant ones. The **theory of human capital** developed by Gary Becker (1964) was the first to theorize the positive association between education and earnings[10] through the assumption that higher levels of knowledge correspond to higher productivity, which competitive markets will reward with higher wages. According to the human capital theory, more years of school make individuals more productive, and this theory is the first to equate educational choices with financial investments. The decision to study, and thus to acquire a certain stock of years of schooling, is a rational decision made by the individual, who foregoes a certain amount of current income in the expectation of a higher income in the future.

More recently, the **theories of skill-biased technological change** (Goldin and Katz 2009) foresee that the demand for education, and hence the supply of human capital, is meant to increase because of the high returns expected from investments in education. The greater complexity of current economic systems requires that the workforce has ever-increasing levels of knowledge and skills in order to cope with jobs and processes that are increasingly complex and interrelated; this leads to a growing demand for high skilled workforce, resulting in better employment and wage opportunities for high skills workers (compared to low skill workers).

Despite the theoretical and empirical emphasis on education (i.e. years of formal schooling) presented so far, it is important to acknowledge and reflect on the broader scope of human capital as composed of educational attainment but also work experience, job training, "soft skills" and, more importantly individual skills. Looking at findings from the National Adult Literacy Survey (NALS), Pryor and Schaffer (1999) distinguished between skills and education as follows: "*Cognitive skills reflect our ability to use reading, writing, and calculating skills to solve problems. Education (particularly as measured by attainment measures) is partly an indicator of what we know, and partly a formal credential attesting to the number of years of formal schooling we have had, and the examinations we have successfully passed… cognitive skills and education play separate and quite distinct roles as determinants of employment and wages*" (pg.11). Educational attainment and skills are not perfect substitutes[11]; while

[9] For a review see: Taylor, Haux, and Pudney (2012).

[10] A major limitation of the existing literature, and therefore a concern researchers should be aware of, is that much of it uses wage or earnings as the dependent variable instead of employment status. While wages and earnings are related to employment status (earnings is a product of wages times the number of hours worked), the factors that impact employment are not the same as those that impact earnings. Thus, while education is an important predictor of employability, specific skills may have stronger impact on earnings.

[11] Previous work undertaken by CRELL further empirically supports this statement, see Flisi, S., Goglio V., Meroni E., Rodrigues M., Vera-Toscano E. 2014. "Occupational mismatch in Europe: Understanding overeducation and overskilling for policy making" Publications Office of the European Union, JRC89712.

formal education is generally seen as the primary agent for the acquisition of knowledge and skills, learning does not solely take place in the school; and while education and labour market experience are both inputs into the production of human capital, neither of them is a direct measure of the outputs. Recent advances in the collection of data on the skills of the working age population through national and international surveys (e.g. PIAAC) have enlarged our understanding of the acquisition of human capital and its economic consequences[12], allowing us to distinguish: 1) the impact of education and experience on skill production and; 2) the relationship between skills and labour market outcomes such as earnings.[13]

To address the issue of skills, education and their impact on employability, Pryor and Schaffer (1999) include both as covariates in their analysis for the United States to find that for people aged 25-49, the probability of employment increases by 3.5 percentage points for men and by 7.2 percentage points for women with each standard deviation increase in functional literacy (skill variable). However, education also impacts employment, though its effects are reduced when literacy is accounted for.

In general, higher levels of skills are associated with higher employment probabilities and higher wages. A study done in early 2000s using UK data from the National Child Development Study (NCDS) (Dearden et al. 2002) shows that having top numeracy skills (Level 1,corresponding to Foundation level in the NCDS) is associated with a two percentage point higher probability of employment. Vignoles, De Coulon, and Marcenaro-Gutierrez (2011), using data from the 1970 British Cohort Study, estimated the association between literacy and numeracy skills and earnings: an additional standard deviation in literacy skills is associated to 14% higher earnings, while an increase by one standard deviation in numeracy skills is associated to approximately 11% higher earnings, with no significant difference between men and women. In addition, they found that the reward for higher skills has remained stable during the late 1990s and early 2000s suggesting that the increase in the supply of literacy and numeracy skills has been matched by the increase in the demand for these skills (ibidem, p. 39), consistently with the skill-biased technological change. Again for the UK, considering adults in their thirties, Bynner and Parsons (2006) showed that men with poor literacy or numeracy were less likely to have a full-time job in the service sector, were less likely to use a computer at work and less likely to receive work-related training from their employer. Similarly, women with poor literacy and numeracy skills were less likely than their higher skills counterparts to be in office-based secretarial/administrative positions, less likely to use a computer at work and to receive training from their employer.

Machin et al. (2001), using data from the British National Child Development Study (NCDS), showed that when compared with soft skills, literacy and numeracy skills have the larger effect: better adult numeracy skills are associated with higher earnings for men, while literacy is the dominant skill for influencing women's wages (ibidem, p. 41). The authors also tested whether an increase in basic skills acquired at adult age translates into an improvement in labour market outcomes, finding that indeed

[12] Green and Riddell (2003) use the Canadian component of the International Adult Literacy Survey (IALS) to investigate the relationship between education, skills and labour market earnings. Hanushek et al. (2013) have provided recent evidence using PIAAC data on returns to skills (earnings) around the world.

[13] Insofar that the relation between education and economic outcomes operates through skills, the key role of education systems in providing such skills and contributing to the sorting effect among individuals in society becomes clearer (Campbell, 2006; Desjardins, 2008).

men who improved their literacy skills (at 37 years compared to skills owned at 16 years old) earn more (compared to those who did not increased their skills) and that an improvement in the level of numeracy skills has positive effects on employment chances (although this effect is stronger for those at the top of the skill distribution).

More recent empirical evidence using PIAAC data shows that in OECD countries better skills are also associated to higher participation in the labour market and to wage premia. Hanushek et al. (2013) showed that one standard deviation increase in numeracy skills is associated, on average in OECD countries, to an 18 percent increase in hourly wage for prime age (35-54) full time workers. The study also shows that returns vary widely across countries[14], with generally lower returns in countries with strict employment protection, high union density and large public sector, and that numeracy and literacy have similar economic returns, higher when compared to problem-solving skills. Besides, they highlight that focussing only on early entrants in the labour market tends to underestimate skill returns, since they are higher for workers in the age range 35-54 compared to labour market entrants (25-34 years), with the only exception of Eastern European countries.

The work by Quintini (2014) confirmed the positive impact of higher skills on occupational chances and wages and a significant heterogeneity among countries. In fact, holding constant the level of education, one standard deviation increase in literacy results in 8% higher probability of being employed (versus unemployed) and one standard deviation increase in literacy proficiency leads to a 20% higher likelihood on average of participating in the labour market, although with sharp country differences (56% for Sweden, 43% for Finland, 15% for Estonia and Poland). Besides, still holding constant the level of education, one standard deviation increase in literacy skills leads on average to an increase in hourly wage comprised between 5% in Denmark, Finland, Italy and above 10% in UK. In addition it has also been found that economic returns associated to higher proficiency tend to increase with the increase of the educational level (although in Poland, Czech Republic, Ireland, the Netherlands, Denmark, France and Estonia returns for low and medium educated are similar; in Italy and Belgium-Flanders upper secondary graduates gain more than tertiary graduates from higher proficiency). But market-related outcomes are not the only positive externalities generated by higher skills. As shown in Dinis Mota Da Costa et al. (2014), higher skill levels are also associated to positive returns in several domains not strictly market-related, as health, trust, and in general social well-being. So far literature highlighted a clear positive relationship between higher educational levels and social outcomes, but the availability of PIAAC data on skills allowed to further investigate the link between higher proficiency levels of literacy, numeracy and problem-solving skills and social outcomes. The work by Dinis Mota Da Costa et al. (2014) shows that low levels of proficiency in the three skill domains assessed in PIAAC are generally associated with lower levels of social outcomes (defined in this work as social trust, volunteering, political efficacy and self-reported health status), although with different intensity across EU Member States. But it also shows that, at least in some countries (as the Netherlands, Denmark and UK), high proficiency levels in skills seem to play a more relevant role than educational attainment: individuals with low educational

[14] Among European countries Ireland, Germany and Spain have returns above the OECD average of 18 percent, while Belgium, Cyprus, Czech Republic, Italy, Norway, Denmark, Finland, Sweden have returns below 15 percent.

level but high skills are more likely to report positive social outcomes than their counterparts with high skills but medium level of education.

It can be concluded that higher levels of skills assure better positioning in the labour market and income, protecting from the risk of poverty in several ways (Taylor, Haux, and Pudney 2012):

a) the higher the level of skills the higher the employment rate, the earnings and the quality of jobs;
b) higher skills make individuals better able to understand social security systems and more able to deal with their own entitlements and claim their rights;
c) better skills are also associated to a better understanding of financial issues, increasing their ability to manage their own resources, reducing the risks related to indebtedness (Taylor 2011);
d) higher proficiency in skills is associated to positive outcomes in the social domain, as social trust, volunteering, political efficacy and self-defined health status;
e) higher literacy rates due to the reduction of low-achievers are also positively associated with less economic inequality[15] (Solga 2014).

2.2.2. Other demographic and socio-economic covariates that may affect employability

To more accurately disentangle the relationship between education, skills and employability, it is interesting to further account for a number of socio-economic and demographic characteristics as control variables which may affect this relationship. On the one hand, certain individual characteristics, such as gender or ethnic group tend to be important predictors of employment status despite the fact that these are inherent traits and neither the individual nor policy makers have any control of them. Likewise, migrant status, while not inherited, is immutable once it occurs. On the other hand, the likelihood of employment is also affected by the individual's family structure, socio-economic status and age which are also likely to affect his/her ability and willingness to work.

Hence, empirical evidence suggests that, on a purely descriptive level, without controlling for any other factors, major significant differences exist in the employment outcomes of women. Women participate less in the labour force (on EU 28 level the gap in the activity rate between men and women is about 12 p.p., see Table A3), work fewer hours, and earn less than men do. While some of these differences disappear when controlling for other important variables such as education, skills, etc. are included, employment outcomes for women may be worse than those for men, ceteris paribus, because of employment discrimination, lower labour force participation, differences that might exist in willingness

[15] Although direct redistribution is more effective in reducing poverty, so that those countries combining investment in skills and direct redistribution perform better (ibidem).

to take part-time as opposed to full-time jobs, differences in the distance women may be willing to travel to find employment, etc. (Altonji and Blank, 1999).

The literature on migrant status and employment is both limited in quantity and ambiguous in findings. From a theoretical perspective, there are offsetting effects to foreign-born status at play. Immigrants may be less likely to find work due to a poor knowledge of the country language or due to more limited social networks and knowledge of the labour market. However, it may also be the case that immigrants arrive in a country for the purpose of taking advantage of the job opportunities available and devoting more time to searching for a job and working (Pryor and Schaffer 1999). The reasons may vary vastly across countries complicating a cross-country comparison.

Empirical research on the determinants of labour supply further indicates that the participation rates of older workers have decreased relative to those of young workers. One interesting feature to this trend is the differential effects between women and men (this is U.S. evidence). Pryor and Schaffer (1999) find that men in the 45-49 age group (reference group is age 25-29) have a 2.6 percentage point decrease in the probability of working, while women in the same age group have a 5.6 percentage point *increase* in the probability of working (pg.39). However, a recent study by Shirle (2008) finds that since the Mid-1990s, male labour force participation has increased for men between 55 and 64. Shirle's evidence suggests that for married men, the single largest predictor of labour force participation is the spousal participation decision.

Taking into account the uniqueness of the PIAAC survey in providing information both on education and directly observed skills, as well as a set of socio-economic and demographic variables, we devote the remaining of this chapter to throw some additional light on the relationship between education, skills and employability.

2.3. Empirical approach

In order to investigate the relationship between formal educational level, individual skills and employment chances, we rely on the use of standard multivariate methods, and in particular (multinomial) logit estimations.

As already mentioned, regressions are carried out using data from PIAAC; consequently, only the 17 European Union Member States[16] that participated in the survey are analysed. We refer to this group as EU 17. For the estimates, 2,014 individuals for which any the variables of interest in our analysis is missing were removed from the original sample. The final working sample is then composed of 102,895 observations[17].

The dependent variable in our logit regressions is a binary variable equal to 1 if the individual is employed and 0 otherwise. The control variables we include in our estimates are age (included as dummy variables for age groups 16-24, 25-34, 35-44, 45-54, 55+), gender, marital status (married/not

[16] Austria, Belgium, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, the Netherlands, Poland, the Slovak Republic, Spain, Sweden, and the United Kingdom.

[17] Sample size by country can be found in the annex, see Table 4.

married), family structure (capturing the presence of children in the household), migrant status (whether foreign- or native-born). We also include parental education as a proxy of socio-economic status, in the form of a dummy variable that equals one if at least one of the parents has a high level of education and zero otherwise. The variables of interest for our analysis are the level of formal educational attainment (low, medium or high[18]) and literacy skill level. We consider four skill level categories, defined on the basis of the proficiency level scale defined in PIAAC; level 1 includes individuals who score at a PIAAC skill level below 1 or 1, levels 2 and 3 mirror PIAAC skill levels 2 and 3 respectively, level 4 includes those who score at PIAAC skill level 4-5 (that are grouped together due to the small number of individuals at PIAAC level 5).

Table 6 below presents all the main variables used in the regressions and reports the proportion of individuals in each category at EU-average level.

[18] Low education corresponds to lower-secondary education or less – ISCED 1, 2, 3C short (ISCED 97, 341 or 351 in ISCED 2011), or less; medium education corresponds to upper-secondary and post-secondary non-tertiary education (ISCED 3-4); and high education corresponds to tertiary education (ISCED 5 or more).

Table 6. Demographic and socio-economic characteristics of the individuals in the sample – EU 17 average

Characteristics	Share
Age group	
16-24	0.196
25-34	0.193
35-44	0.199
45-54	0.197
55 +	0.213
Gender	
Female	0.524
Marital status	
Married	0.588
Family structure	
Presence of children in household	0.613
Parental education	
High level (at least one of the parents having high education)	0.616
Migrants	
Foreign-born	0.102
Educational attainment	
Low Education	0.225
Medium Education	0.473
High Education	0.300
Occupation (for employed individuals only – sample size =67,099)	
Professional occupation	0.438
Semi-professional, white collar occupation	0.274
Semi-professional, blue collar occupation	0.207
Unskilled occupation	0.079
Literacy skills level	
Level 1 or below 1	0.153
Level 2	0.339
Level 3	0.390
Level 4 and 5	0.116
N = 102,895	

Source: Own calculations on our working sample from PIAAC (2012).

Before going into the results of the analysis, it is worth pointing out an important caveat. The approach we adopt is aimed at estimating the association between education/skills and employment status, after controlling for some observable characteristics that could affect labour market outcomes; however, this does not mean isolating the causal impact of human capital on employment. Human capital and employment are two strictly connected factors that are likely to be influencing each other. While it is reasonable to assume that higher formal qualifications and higher skills can translate into better employment prospects, it is also possible that the condition of being employed itself fosters individuals' skills; the relationship between skills and employment is therefore likely to go both ways. With the data available, it is not possible to solve this endogeneity issue, since the lack of longitudinal information and valid instruments prevents us from yielding consistent estimates on the causal impact of education and skills on the likelihood of employment. While it is important to bear this caveat in mind, we believe it is in any case worth exploiting the information provided by PIAAC to further investigate the association between education, skills and employment across EU countries participating in the survey.

2.4. Results

2.4.1. The effect of formal education and literacy skills on employment opportunities

As a first step in the analysis of the relationship between formal educational qualifications, skills and employment chances, we rely on standard logit regressions and use two different specifications. The dependent variable is always a binary variable equal to 1 if the individual is employed and 0 otherwise. Both specifications include the control variables detailed in Section 2.3 (age, gender, marital status, family structure, migrant status and parental education). In terms of our variables of interest, the first specification (our baseline one) includes education attainment only; as a next step, in the second specification we control also for proficiency in literacy skills: this allows us to check how the effect of formal education changes depending on whether we take into account the level of individual skills.

Table 7 presents the logistic regressions estimated on the pooled EU 17 sample. Estimates include country fixed effects in order to remove the effect of country-specific characteristics. The first specification is reported in column 1, the second in column 2. Table A5 to Table A10 in the Appendix present the results of both specifications by country. The reference category in the estimates is individuals in the age group 35-44, with low education level, and low literacy skill level 1.

As can be seen in the first column of Table 7, the level of formal education is positively and significantly related to employment: the higher the level of educational attainment, the higher the likelihood of being employed.

When adding skills level in literacy to our baseline model, we see an interesting result: as shown in column 2, the variables representing skill levels (here, skill levels higher than the base one, which includes those with very low skills) enter the equation with positive and significant signs, with the two highest skill groups (3, 4 and 5) having a consistent premium when compared to skill level 2. If we calculate the odds ratios from the coefficients[19], we find that, other things being equal, an individual in skill level 2 has a 25% higher probability of being employed than someone in the lowest skill group; individuals with literacy skills at levels 3, 4 and 5, on the other hand, have a 44% higher chance of employment than the base group. What we can also notice, however, is that the inclusion of the skill level variables in the regressions leads to a reduction in the positive effect of formal education, as shown by the lower coefficients of the dummies concerning medium and high education in the regression; this suggests that part of the effect of education indeed works through individual skills.

Table 7. Education and skills effects on employability – Pooled sample (EU17)

Specification	*(1)*	*(2)*
Literacy skill level 2		0.227***
		(0.037)
Literacy skill level 3		0.371***
		(0.039)
Literacy skill level 4 and 5		0.368***
		(0.055)
Medium education	0.713***	0.655***
	(0.032)	(0.033)
High education	1.341***	1.222***
	(0.039)	(0.041)
Age group 16-24	-1.524***	-1.553***
	(0.050)	(0.050)
Age group25-34	-0.255***	-0.258***
	(0.044)	(0.044)
Age group 45-54	-0.0156	-0.00227
	(0.043)	(0.043)
Age group 55-64	-1.438***	-1.410***
	(0.040)	(0.040)
Female	-0.675***	-0.678***
	(0.025)	(0.026)
Married	0.485***	0.473***
	(0.032)	(0.032)
Presence of children in the household	-0.117**	-0.104**
	(0.037)	(0.037)
High parental education (socio-economic background)	0.0748*	0.0346
	(0.031)	(0.031)
Foreign-born	-0.370***	-0.300***
	(0.045)	(0.046)
Constant	1.048***	1.091***
	(0.063)	(0.065)
N	102895	102895

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. Both specifications include country dummies. All figures are weighted.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

[19] Coefficients from logistic regressions are expressed in log-odds units, which makes them difficult to interpret; in order to make interpretation easier, coefficients are generally converted into odds ratios, which is done by exponentiating the coefficient itself.

Table 7 further allows seeing which socio-economic characteristics increase the probability of employment. In general, results are in line with the evidence provided by the literature; younger (16-34 years) and older (55-64 years) cohorts appear to be less likely to get a job than prime-age individuals in the age group 35-54, suggesting an inverted U shaped curve for the relationship between age and employability. Employment chances are lower for the foreign-born than for natives; female employability is consistently lower than for males; being married seems to be associated to higher employment chances, while the presence of young children in the household appears to reduce them. The effect of socio-economic background, here proxied by parental education is not significant.

The results just described at pooled level potentially hide important cross-country heterogeneity, which may be worthwhile exploring. Accordingly, we discuss now the main similarities and differences found in the analysis at country level. As mentioned, Table A5 to Table A10 in the Appendix present the results of both specifications with the full set of covariates by country.

For all countries education is a significant determinant of employment; the higher the level of formal educational attainment, the higher the premium on the chances of employment of the individuals when compared to the low educated, as can be seen in the consistent differences in the coefficients for medium and high education. However, when we include in the regressions dummies for literacy skill levels, diverging patterns emerge across countries.

For a first group of countries, namely DE, DK, EE, ES, FI, IE, SE and UK, the evidence suggests a consistent and significant positive relationship between higher skills level and the probability of employment. For EE, this holds for higher skill levels (3, 4 and 5), while for skill level 2 employment chances do not appear to be significantly different from the omitted category (level 1 or below). The introduction of controls for skill level generally leads to a reduction in the effect of education, as in the regression for the pooled EU sample. A second group of countries, consisting of AT, CY, CZ and PL, shows no significant impact of skills on employability. We can include in this category also IT, for which only a rather weak effect of skill level 3 emerges, but overall no consistent impact of skills on employability emerges. The lack of significance in the skills-related covariates seems to suggest that in these countries formal education is more important than current skills in explaining individuals' chances of employment.

Finally, the remaining countries display mixed results, with no clear pattern emerging. In BE and FR, skill level 2 seems to grant a significant employment advantage on those with skill level 1 or below, while quite counterintuitively, higher skill levels do not appear to produce the same positive contribution to employability (except for a weakly relevant positive effect for the highest skill level for BE). For NL and SK, only skills at proficiency level 3 seem to yield a premium in terms of employment chances, while no effect is found for level 2, 4 and 5 (except for a weak effect of level 2 for SK). This contrasting evidence is hard to interpret, and further analysis (out of the scope of this report) might allow a better understanding of the phenomenon.

2.4.2. The impact of education and skills on type of occupation.

The previous section shows that skills have a positive effect on employability, although not in consistent way across skill levels and countries. Starting from this result, as a next step it would be interesting to investigate whether not only the chances of employment, but also the type of job one finds, can be affected by the level of individual skills. For this purpose, we select the sub-sample of individuals who are currently employed, and on this reduced sample we run a multinomial model using as main dependent variable occupation, measured through 4 possible alternatives, i.e. skilled occupations, semi-skilled white collar occupations, semi-skilled blue collar occupations, and unskilled occupations[20]. This is done to disentangle whether the impact of individual literacy skills on employability vary across occupations. This exercise further allows us to combine individual skills (labour supply) to type of occupation (as a proxy of labour demand). Table 8 reports the results for the multinomial logit analysis on the pooled sample of the 17 EU countries, while Table A11 to Table A13 present the results by country. We show in the tables only the coefficients for the variables of interest, i.e. level of skills and formal education. We do not report estimates for the control variables, namely age group, gender, marital status, family structure, parental education, migrant background, and country fixed effects (for the pooled sample).

As mentioned, the dependent variable has 4 possible outcomes; the multinomial logistic regression will estimate 3 models, where the estimated parameter for each explanatory variable is relative to the chosen reference category; in this case, the excluded category is unskilled occupation, thus all coefficient should be interpreted as probabilities of being in a given category rather than being in an unskilled occupation.

As expected, the results reported in Table 8 show that, for the pooled sample (EU 17), individuals with higher level of skills are significantly more likely to be employed as skilled professional, semi-skilled white collar and semi-skilled blue collar occupations rather than as unskilled workers compared to those with no skills (Literacy skill level 1 or below). As can be noticed in the coefficients, the higher the skill level, the higher is the probability of being employed in a skilled or semi-skilled white collar occupation rather than in an unskilled one. Thus, for example, the estimated coefficient for literacy skill levels 4 and 5 is small and non-significant for semi-skilled blue collar occupations (0.271) whereas it increases to 2.153 becoming significant for professional occupations. This result may indicate that individual actual skills, beyond formal education, play a greater role as the level of competences increases by type of occupation. A similar pattern can be found for the level of formal education: a higher qualification grants a higher probability to be employed in a skilled occupation rather than a less skilled one, and

[20] Skilled occupations include occupations under ISCO 1 digit classification 1, 2 and 3, e.g. legislators, senior officials and managers; professionals; technicians and associate professionals; semi-skilled white collar occupations include e.g. clerks, service workers, shop and market sales workers (ISCO 1 digit 4 and 5); semi-skilled blue collar occupations include e.g. skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators and assemblers (ISCO 1 digit 6, 7 and 8); unskilled (or elementary) occupations cover ISCO 1 digit 9, such as labourers.

even the premium associated to tertiary education when compared to secondary increases for more highly skilled types of occupation.

Table 8. Education and skills effects on type of occupation – EU 17 (Multinomial logit)

	EU17
Skilled occupations	
Literacy skill level 2	0.798***
	(0.080)
Literacy skill level 3	1.393***
	(0.085)
Literacy skill level 4 and 5	2.153***
	(0.152)
Medium education	1.624***
	(0.079)
High education	3.923***
	(0.115)
Semi-skilled white-collar occupations	
Literacy skill level 2	0.439***
	(0.069)
Literacy skill level 3	0.718***
	(0.077)
Literacy skill level 4 and 5	1.046***
	(0.151)
Medium education	1.006***
	(0.067)
High education	1.687***
	(0.110)
Semi-skilled blue-collar occupations	
Literacy skill level 2	0.273***
	(0.071)
Literacy skill level 3	0.269***
	(0.081)
Literacy skill level 4 and 5	0.271
	(0.165)
Medium education	0.562***
	(0.069)
High education	0.701***
	(0.119)
N	67,099

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: low education level, literacy skill level 1 or below. The regression includes controls for age group, gender, marital status, family structure, parental education, migrant background, and country dummies. Reference category for the multinomial model: unskilled occupation.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

When looking at the estimates by country (Table A11 to Table A13), we find confirmation of the overall patterns, although with some differences emerging. A consistent result concerns formal education: as for the pooled sample, across all countries we find that higher qualifications are associated to higher probabilities of having more skilled jobs, and that the premium of having tertiary rather than secondary level education is significantly higher the more skilled the occupation is. As far as the effect of literacy skills is concerned, we find that for all countries, a higher skill level translates into higher chances of being occupied in skilled occupations (the only exception being CY, for which no significant skills-related effect arises in the regression). Skill levels 3 and 4/5 have a particularly strong and significant effect in this sense, but in most countries a premium is associated also to skill level 2. For 10 out of the 17 countries, namely BE, CZ, DK, FI, FR, IT, NL, SE, SK and UK, higher skill levels are also associated to higher probabilities of working in semi-skilled white collar occupations, rather than unskilled ones, although in this case the coefficients are overall smaller than in the previous case.

This new evidence confirms that, besides education attainment, skill level is relevant in determining chances of labour market success, in terms not only of employment, but also of the type of occupation that an individual can get. This section adds to the results provided in the previous one, where we highlighted a few countries where skills appeared not to increase employability (AT, CY, CZ, IT, PL), or where contrasting results emerged (BE, FR, NL, SK); even in these countries, while higher skills might not contribute to raising employment chances, they do seem to favour labour market performance in terms of the type of occupation that the individual can get. It is possible that in such countries, formal educational qualifications are what matters to gain employment; nevertheless, not only education, but also individual skills, become important when it comes to obtaining a better occupation[21].

2.4.3. The relationship between education and skills: A look at the average predicted probabilities

The results presented in the previous sub-sections allowed seeing the correlation between the outcome variable, employment, and human capital related variables (education and literacy skills). However, these correlations are independent from each other, in that they measure, for instance, the effect of a specific skill level, holding constant the education level, and the other way around. While this analysis was interesting to understand whether skills had a separate effect from the already attained education level, it is also informative to study the relationship between these human capital dimensions. We do so in this section, by computing the predicted probability (at the means of all other covariates) of different mutually exclusive groups of individuals defined by the human capital variables.

[21] In order to check whether skills favour individuals in the way they progress towards better jobs once they are employed, longitudinal data would be required. As already mentioned, lack of data prevents us from carrying out more detailed analysis on the evolution of the relationship between skills and labour market performance over time.

In order to facilitate this exercise we consider only two levels of literacy skill proficiency. In particular, high skilled corresponds to PIAAC skill levels 3 to 5, and the others are considered low skilled (former literacy levels 1 or below and 2). The education variable is defined in the same way as before (low, medium, high and see Table 9 summarizing the different grouping of skills).

Table 9. Aggregation of PIAAC skill levels adopted in the analysis

PIAAC skill levels	Skill levels used in the regression (Table 7 and Table 8)	Skill levels used for predicted probabilities (Table 10, Table 11, Figure 7)
1 or below	1 or below	low
2	2	
3	3	high
4	4 and 5	
5		

Thus, individuals are allocated to one of the six groups shown in Table 10[22]:

Table 10. Groups combining education and skill level

	Education level	Skill level
Group 1 (EL-SL)	Low	Low
Group 2 (EL-SH)	Low	High
Group 3 (EM-SL)	Medium	Low
Group 4 (EM-SH)	Medium	High
Group 5 (EH-SL)	High	Low
Group 6 (EH-SH)	High	High

This analysis is extremely informative in the sense that it allows judging which of the human capital dimensions contributes the most to employment. In fact, while the regression coefficients are not to be compared across variables, one can directly compare the predicted probabilities of the different groups.

[22] In order to have a complete picture about the level of skills per each educational level, we provide here a table with the share of individuals with high/low skills per each educational level:

		Education level			
		Low	Medium	High	Total
Skill level	Low	20.4	26.66	8.06	55.12
	High	5.75	19.94	19.19	44.88
	Total	26.15	46.60	27.25	100

To perform this exercise, we need to start from regressions based on the same categories we are now taking into account; we therefore run again the logit regressions by country, considering only two possible levels of skill (low and high)[23], then from these estimates we calculated the predicted probability of being employed rather than out of employment.

Table 11 reports the predicted employment probabilities by country and education/skill group. In order to facilitate interpretation, we present them in Figure 7. The red bars represent the low education group, the green ones represent medium education, the blue ones high education; within each of these pairs of bars, the first one (with the lighter colour) shows the predicted employment probability of those with low skills, the second one (with the stronger colour) that of highly skilled individuals. The bars are therefore displayed in what can be considered as an order of 'increasing' education/skill combination. The focus of our analysis is not so much on comparing the levels of employment across countries, which can vary depending on the labour market and overall economic situation, but rather on comparing, within each country, performances across the different education/skill categories; practically speaking, this means we are interested in observing the 'shape' of the bars for each country considered. If the bars display sort of an 'upward' shape, this means that higher formal education is associated to higher level of employability, and that higher skills grant an employment premium which is however not as strong as the one produced by education. A big jump between subsequent pairs of bars (i.e. between the red and the green ones, or the green and the blue ones) shows that education provides a consistent employment advantage; a jump within pairs of bars, i.e. between the light red (green/blue) one and the red (green/blue) one, represents an employability premium produced by skills.

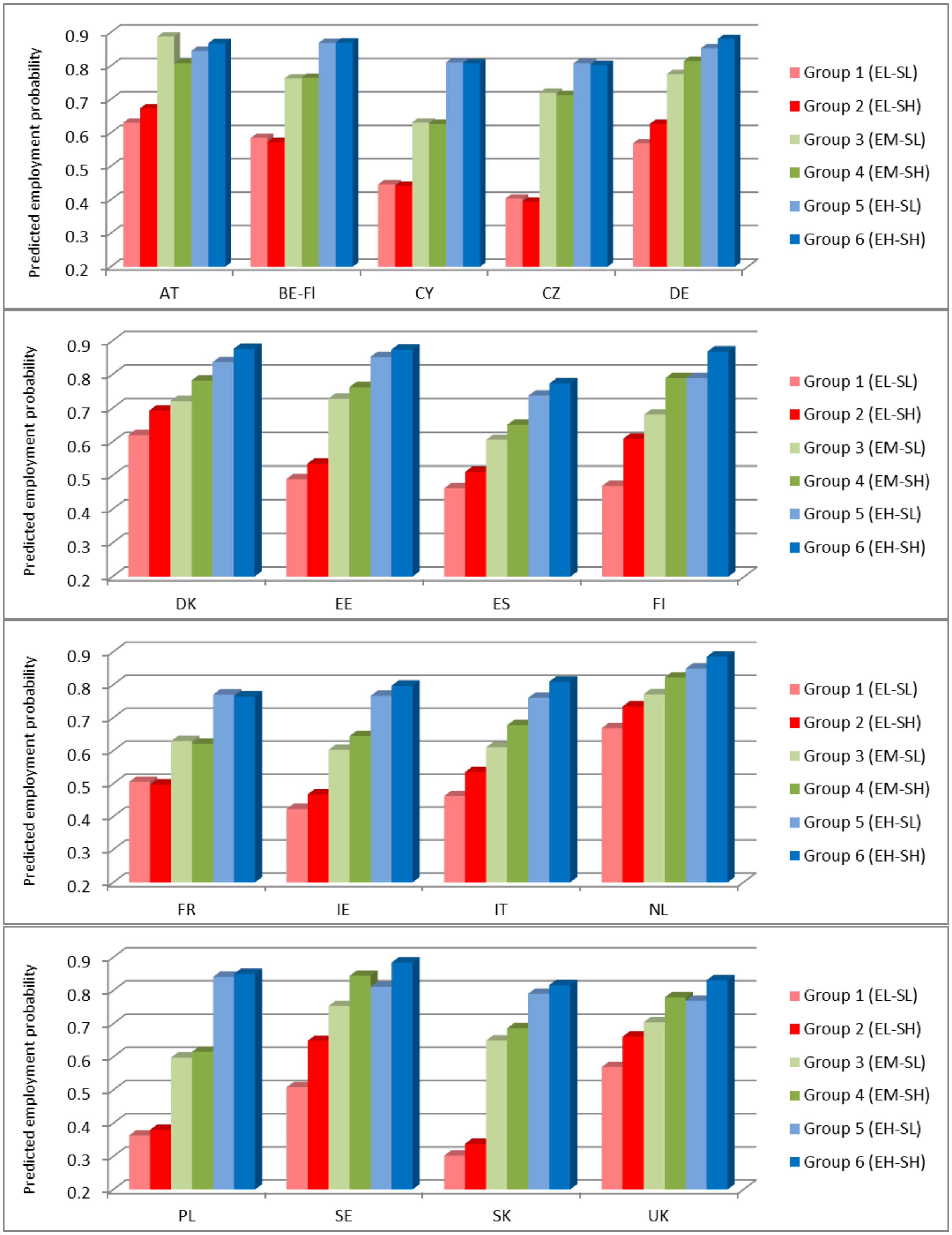
[23] It is worth mentioning that when running again these regressions, a couple of changes arise in the coefficients concerning skills. For most of the countries, the patterns found are the same; however, for AT and IT, a significant impact of high skills on employability is found, while in the regressions discussed previously in the chapter, no relevant effect emerged for AT, and only a weak one was registered for IT. This can be explained by sample size issues, since when aggregating individuals in 2 categories (high/low skills), instead of 4 as before (skill levels 1 to 4), the sample size for each group increases.

Table 11 Predicted probability of employment by group and country

	Group 1 (EL-SL)	Group 2 (EL-SH)	Group 3 (EM-SL)	Group 4 (EM-SH)	Group 5 (EH-SL)	Group 6 (EH-SH)
AT	0.631	0.674	0.888	0.808	0.845	0.868
BE-Fl	0.585	0.573	0.763	0.765	0.869	0.870
CY	0.446	0.442	0.631	0.627	0.811	0.808
CZ	0.404	0.395	0.720	0.713	0.808	0.803
DE	0.569	0.627	0.776	0.815	0.853	0.881
DK	0.620	0.693	0.721	0.782	0.836	0.876
EE	0.489	0.535	0.728	0.762	0.852	0.874
ES	0.462	0.511	0.606	0.651	0.737	0.773
FI	0.469	0.609	0.681	0.789	0.789	0.868
FR	0.505	0.497	0.629	0.621	0.770	0.764
IE	0.423	0.467	0.602	0.644	0.766	0.797
IT	0.462	0.535	0.610	0.677	0.760	0.809
NL	0.668	0.734	0.771	0.822	0.849	0.885
PL	0.363	0.380	0.598	0.615	0.841	0.850
SE	0.508	0.648	0.753	0.844	0.811	0.884
SK	0.302	0.338	0.649	0.686	0.790	0.816
UK	0.569	0.661	0.704	0.779	0.769	0.831
EU	**0.515**	**0.628**	**0.675**	**0.729**	**0.781**	**0.822**

Note: PIAAC 2012 data, own computations. The table presents the predicted probabilities of employment for the six groups of individuals defined in Table 10. SL and SH stand for 'Skill level Low' and 'Skill level High', respectively. EL, EM and EH stand for 'Education level Low', 'Education level Medium' and 'Education level High', respectively.

Figure 7. Average predicted employment probabilities by level of education and level of literacy skills



Note: own calculations on PIAAC (2012).

Overall, there is a quite clear upward trend that characterises many countries. A perfect example of this is DK, where each increase in education or skills produces a similar increase in employability. The group of countries following an analogous trend includes DE, EE, ES, IE, IT, NL and SK; the relative importance of an increase in education or skills can however vary, so that for example in EE and IE the relative weight of education appears bigger, as shown by the higher jump between pairs of bars than within them. It can be said that in these countries higher levels of actual skills seem to be acknowledged on the labour market, providing the worker with an additional premium to the original advantage coming from the educational level only.

For a second group of countries, that includes BE, CY, CZ, FR and PL, the only visible effect concerns education, meaning that for the same level of formal qualification, having high rather than low skills has no impact on the chances of employment. Finally, there are three countries representing special cases of skills being extremely relevant in determining employability. FI, SE and UK are characterised by the same patterns we found for most other countries, i.e. both an education and a skill premium in determining the probability of being employed, however, in these three countries, individuals with medium education but high skills display a level of employability equal to (for FI) or higher than tertiary graduates with low skills, suggesting that in this case, additional skills can even make up for not having a university degree[24].

These results seem in line with the trend identified by van de Werfhorst (2011) about returns to skills. Although he focused on the effect of skills on earnings, some of his findings turn out to be useful also in interpreting our results about employment chances. In fact, he found that the effect of skills on earning is smaller in countries with well-developed vocational sector within their educational system, based on the fact that in these countries there is less uncertainty among employers about the skills that can be expected from workers with a particular educational qualification; thus in this context, additional indicators of productivity (like skills) are considered less important for determining earnings (ibidem, p. 1088). Since in his work BE, CZ, FR and PL are defined as vocationally oriented, our analysis showing that the effect of skills is not observable in these countries, seems to be in line with his findings. Similarly, his findings also seem to be useful for interpreting results for FI, SE and UK, in his work identified as less vocationally oriented (compared to the previous countries), and thus more likely to reward additional indicators of skills rather than educational qualifications only.

[24] AT is the only outlier in this analysis, showing that individuals with middle level education not only are advantaged compared to those with the same level of education and higher skills, but also to those with tertiary education.

2.5. Conclusions

In this chapter, we tried to investigate the relationship between formal education, skills and employment in the working age population of EU 17 countries.

Cross-country evidence supports the widely acknowledged fact that higher levels of education are correlated to higher employment probabilities and with more skilled types of occupations. However, our analysis also shows that, together with formal educational qualifications, skills do exert an important effect on the individual labour market performance.

As shown in Section 2.4.1, for DE, DK, EE, ES, FI, IE, SE and UK, our analysis suggests a consistent and significant positive relationship between higher skill levels and the probability of employment; while for the other countries the evidence in this sense is less clear (with AT, CY, CZ, IT and PL displaying no significant effect, and BE, FR, NL and SK showing mixed results). Besides, in Section 2.4.2 we show that all countries (except CY) present a positive impact of the level of skills on the type of job an employed individual can get: a higher skill level appears to translate into higher chances of being employed in skilled rather than unskilled occupations.

The exercise we carry out in Section 2.4.3, aimed at getting a better grasp of the interaction between education and skills effects, further confirms that for a big group of countries (namely DK, DE, EE, ES, IE, IT, NL and SK), both education and skills contribute positively to employment chances. However, it also highlights that the impact of formal education is stronger than that exerted by skills: while it is true that a higher level of skills (within the same educational qualification) grants an employability advantage (compared to those with the same educational level but lower skills), the premium provided by a higher level of formal qualification is anyway greater (as an example, an individual with medium level of education and high skills has a lower predicted probability than an individual with higher educational level but low skills). Section 2.4.3 also shows interesting differences in the paths found for other groups. In particular, it emerges that in BE, CY, CZ, FR and PL, only education has a visible effect, while, given a certain level of formal qualification, having high rather than low skills has no impact on employability. On the opposite extreme, FI, SE and UK are perfect examples of situations in which a high level of skills has the same – or higher – effect than a higher level of formal education, so that among those with medium education, the highly skilled appear to have higher chances of employment than the low skilled with a tertiary degree. These interesting results highlight the importance of both formal qualifications and actual skills for good labour market outcome.

To properly investigate the relationship between the evolution of skills over the life time and labour market outcomes, we would need longitudinal microdata that is currently not available. Despite the impossibility to establish a real causality link between skills and employment with the data available, the evidence provided in this Chapter shows that a relationship does exist, and that it does not work only through formal education. This is an interesting piece of information, since education attainment remains the same throughout life after leaving the education system, skills continue to evolve, and this can happen following different trajectories. Skills, and not only education attainment, are therefore fundamental to represent the individual's level of competences and human capital. First, because individuals with the same level of education may have different skill levels – e.g. due to innate ability or differences in the quality of education; second, because skills develop over time, for instance increasing with work experience or informal education, or decreasing as a result of ageing or depreciation of specific abilities. For these reasons, the next chapter will be devoted to investigate how and to what extent skills evolve over time, in an attempt to identify the main drivers of change in the skill composition within countries.

Chapter 3. Skills deterioration and skills gain. An analysis of the drivers of skills change

3.1. Introduction

The importance of skills for successful labour market participation has been studied in Chapter 3. In addition, previous literature has underlined that owning higher skills is not only fundamental for better labour market outcomes, but also for many other aspects of social and economic life, e.g. better health status, reducing crime, increased trust and participation in politics. Skilled individuals are more able to process information and to use their knowledge to take decisions. They are also more able to judge how their performance may affect future generations, thus contributing to the overall stability and well-being of societies.

Policy makers in most developed economies are alarmed about the risks of skill obsolescence in the modern "knowledge economy". Besides the decline of cognitive abilities of an increasingly ageing population, the risk of skill obsolescence is also particularly important in many industries and sectors that use rapidly changing technologies. One of the major concerns is that such skill deterioration will lead to increasing skill mismatch and job insecurity over the life course, making it difficult to maintain an adequate level of labour market participation of less skilled individuals.

Therefore, it is important to better understand not only the level and distribution of skills (as seen in Chapter 1), but also how individuals (and the population) gain, lose and preserve their skills over time. In this chapter we review the existing literature on the drivers of skill change and provide empirical evidence on two main aspects that can influence the change in the skill level of a population, namely the ageing effect and the cohort effect, investigating also how education plays a role in the dynamics of skills change. Furthermore, given the increasing interest in the phenomenon of lifelong learning, as a possible solution for the problem of skill deterioration, results are also presented taking into account how the participation in lifelong learning could mitigate possible skill loss.

3.2. An overview of the main drivers of skill change

From an economic point of view De Grip and Van Loo (2002) distinguish two types of drivers of skill change[25]. According to the authors, human capital may depreciate due to *technical* and *economic* skills deterioration (see Table 12).

[25] See also Arthur et al. (1998) for a thorough literature review on the factors that influence skill decay and retention, and Desjardins and Warnke (2012) for a broader view on the classification.

Table 12. Types of skills deterioration

Type of skills deterioration	Depreciation of human capital by:
Technical	
a) Wear of skills	Natural ageing process, illness or injury
b) Atrophy	No or insufficient use of skills
Economic	
c) Job-specific skills deterioration	New skill requirements due to development in society
d) Skills deterioration by sectorial shifts	Shrinking employment in occupation or economic sector
e) Firm-specific skills deterioration	External mobility due to firm closure or reorganizaton

Source: De Grip and Van Loo (2002).

Technical deterioration affects the ***stock*** of human capital a worker possesses in the sense that skills get lost. The broad concept of "normal ageing" is used in the literature to identify the process by which some cognitive functioning (as a component of human capital) tends to deteriorate with increasing age. While a general trend of downward development of skills has been observed (Hertzog et al. 2009), research has also shown that the trend is not uniform across all individuals and across all types of cognitive skills, with several factors influencing the speed and the extent of the process of skill deterioration, including neurological and behavioural maturation. The former refers to the biological and neurological aspects of the brain: studies in the field of cognitive ageing have shown that ageing is associated to both structural change (decline in brain volume in specific areas and amount of gray and white matter) and functional change (different patterns of neuronal activation compared to young people) (Desjardins and Warnke, 2012, p.13). However, these processes interact with practices and behaviours performed by individuals, so that not all individuals are evenly affected by neuro-biological factors. Social and economic characteristics of the environment in which the individual lives can play a significant role in preserving or even increasing the level of skills: according to the "use it or lose it" hypothesis, skills are comparable to muscles, subject to atrophy if not regularly and properly exercised. Analysis carried out using PIAAC data (European Commission 2014) adds empirical evidence supporting the positive link between the use of skills at work and higher employees performances in skill proficiency.

On the other side, the overall cultural capital of the *family* and of the *social relationships* as well constitute a "nurturing environment", offering different quantity and quality of intellectual stimuli, reinforcing or compensating for schooling (Desjardins and Warnke, p.14). Together with family and social ties, the *working environment* is also crucial in avoiding skill loss and preserving skills through time. In fact, individuals involved in jobs requiring the use of specific skills tend to reinforce those skills (for instance, people with a job requiring lot of reading and writing activities tend to reinforce their literacy skills compared to those with a job not requiring it).

Similarly, economic skills deterioration affects the ***value*** of the human capital a worker possesses due to external and rapid developments. Thus, for example, the risk of skill decay is thought to be particularly great in industries that use rapidly changing technologies and where the skills the workers in those industries possess are probably no longer sufficient to perform their jobs properly.

Within this double classification, technical factors are those that refer to the individual level, and that can be modified in the training or learning context to reduce skill loss. On the other hand, economic factors are inherent features of the job/task, and typically not open to modification. However, this latter set of factors could be embedded into a broader classification of factors affecting skills decay and preservation that can be quantitatively measured and which go beyond the economic domain, that is, *social factor*[26]. Individuals come into contact with a variety of contexts beyond the workplace, including the family, the school or the community. These contexts, with their physical environments as well as the social, cultural and technological conditions under which individuals come to experience them, are subject to change over time. This means that an individual aged 40 today may not be entirely comparable to one aged 40 in ten years from now. Such changes bring about the potential for cohort effects to skill development and while changes of this nature are outside the control of any individual, they may nevertheless affect his skill development trajectories. More specifically, the effect of these events on the pattern of skill development can be *indirect*, affecting the set of opportunities available to individuals (as in the case of wars, famines or cultural changes as the mass diffusion of news), but also *direct*, as in the case of national reforms regulating the access to compulsory education or changes in teaching practices or curricula, which directly influence the quantity and quality of skills transmitted by formal education (Desjardins and Warnke 2012). Thus, understanding how the ageing (as the most significant driver of skill change within the technical/individual type) and cohort effect interact and how they contribute to shape the skill levels of the European countries is fundamental for policy makers, so as to ensure that their citizens are endowed with the level of skill required to reach their individual wellbeing, and to increase prosperity and growth in the overall society.

3.2.1. The key role of ageing and cohort effects

Several authors addressed the topic of ageing and skill development trying to disentangle the complex relationship between age and cohort effects.

Before reviewing some of the most interesting findings available in the literature, it is important to clarify that several types of intelligence (or skills) have been investigated (Cattel 1987, Baltes 1993) and that the impact of individual and social factors varies a lot according to the measure of intelligence analysed. For the sake of our work we refer here to the distinction drawn between *basic cognitive skills* (perceptual speed, memory, spatial orientation, etc.) and *cognitive foundation skills*, which correspond to the type of skills (literacy, numeracy, problem solving) measured by international programs such as PISA, PIAAC, IALS, ALL (Desjardins and Warnke 2012). Empirical research has shown that the pattern of development of *cognitive foundation skills* is characterized by a deterioration of skill level with increasing age, which starts already in the mid-20s. Studies on the Canadian adult population showed that the middle-aged population experiences a significant literacy skill loss (Willms and Murray 2007)

[26] Parallel to De Grip and Van Loo's classification of ***technical*** and ***economic*** factors, Desjardins and Warnke (2012) distinguish between ***individual*** and ***social*** factors affecting the pathway of skill development.

and that, even controlling for education and immigration, individuals younger than 46 years old showed a decline in literacy skills (Green and Riddell 2013).

However, comparative studies highlighted that literacy skills vary across countries, suggesting that structural factors at country level (as the distribution of educational attainment, the structure of the education system and of the labour market) can also affect the pathway of skill development, even leading to literacy gains in some cases (Cascio, Clark, and Gordon 2008).

Studies performed using IALS and ALL data confirm the negative relationship between literacy and ageing, and that when controlling for level of education, the older cohort performs lower already since the age of 16, although differences are small up to 50 years old (Desjardins and Warnke 2012).

More recently, Green and Riddell (2013) confirmed that the negative relationship between literacy and age starts quite early. Formal education is the main means through which skills are acquired, after which not only individuals do not further develop literacy skills, but they gradually and slowly deteriorate their skill endowment. Nonetheless, the negative relationship between skills and age is not entirely attributable to age per se, but rather it is the result of a combination of age and cohort effect. Using IALS and IALSS[27] data for Canada, USA and Norway, the authors show that not only literacy skills deteriorate with age, but also that more recent birth cohorts have lower levels of literacy skills compared to older ones.

Another important finding is that the decline in literacy skills is not homogeneous across the skill distribution but rather, it can affect differently those at the top (high initial level of skills) or at the bottom (low initial level of skills), and this can vary across countries. As an example, in Canada the skill loss affects more strongly those at the top of the distribution: this implies that those with high levels of skills tend to lose skills more than those with initial low levels. On the contrary, in Norway those at the bottom of the distribution are more affected, meaning that people with already low levels of skills tend to lose more than those with high levels, thus further widening the gap between bottom and top performers, and worsening their already low occupational chances. Finally, in the USA the deterioration of skills due to age and cohort effect mainly affects those in the middle of the distribution (having a medium level of skills).

The differential impact of the deterioration of skills on individuals with different original capabilities justifies the need of a deep investigation of the topic: for this reason and bearing in mind the priorities of the strategic framework for European cooperation in education and training (ET2020) this report will also pay particular attention to the category of low achievers, here broadly defined as those at the bottom of the distribution (10th quantile of the distribution of skills) (see quantile analysis in Sections 3.6-3.7).

To conclude, as several studies have shown, policy can make a difference in contrasting age-related deterioration of skills. Thus, we present here a brief review of the evidence related to factors that can

[27] IALSS is the 2003 International Adult Literacy and Life Skills Survey.

intervene in mitigating the deterioration of cognitive skills due to ageing process (Desjardins and Warnke 2012):

a) Initial formal education:

Higher educational attainment is positively associated to the level of skills of adults, it predicts the maintenance of high cognitive functioning in old age.

b) Lifelong training:

Since most of the skill loss can be attributable to skills underutilization, task specific training (not general one) has been found to positively mitigate the deterioration of cognitive skills. However, it has also been found that cognitive training is more effective among individuals with already high performances (top quantiles). We will go back to this approach to skill preservation and acquisition later on.

c) Physical and social activity:

Physical exercise has been found to have a positive effect in lowering down the risk of experiencing age-related deterioration of skills, in particular the abilities of planning, working memory and multi-tasking. On the contrary, smoking and psychological stress are found to be associated to cognitive decline.

As far as social activity is concerned, it has been found that loneliness is positively associated to cognitive decline, while elders engaged in a socially active lifestyle have a generally reduced risk of deterioration of skills.

d) Occupation:

The mental activity associated to jobs requiring high cognitive skills and job complexity are found to exert a positive effect on the growth rate of skills, and on decreasing the risk of experiencing dementia and Alzheimer. On the contrary, retirement has been found to have a causal effect on cognitive decline.

For many countries, ageing is one of the main social and economic challenges of the current century. In Europe, for example, the ratio of people aged 65 and over as a percentage of the population aged 18–65 is expected to increase dramatically in the next 50 years (Eurostat, 2013). In addition, countries are facing another threat: are the new generations leaving formal education with higher or lower levels of skills? Have the massive education expansion policies implemented in most European countries been effective in raising the skills of the younger part of the population? Understanding how the ageing and cohort effect interplay together and how they contribute to shape the skill levels of the European countries is fundamental for policy makers, so to ensure that their citizens are skilled enough to increase prosperity and growth in the overall society, at the same time reaching individual fulfilment.

All in all, there are at least three major reasons for focusing on the connection between age, cohort and skills. First, skills are not fixed after formal education is received and, while skills can increase as a result, for example, of work experience, they can also be lost due to lack of use. In the context of an ageing workforce, understanding the relationship between ageing and skills becomes crucial. Second, beyond labour market interests, skills are also important for the successful participation of older adults in a broader social, political and cultural life. Thus, the maintenance and use of certain skills may have important consequences on individuals' quality of life and overall well-being. Last but not least, research on adult skills matters because of the growing policy interest in monitoring educational investment. Indeed, the key issue to disentangle is whether increased rates of educational attainment across EU 17 countries are also linked to an average higher level of skills. Policy efforts need to be geared towards ensuring optimal skill formation over the lifetime, increasing the opportunities for productivity and growth.

The availability of PIAAC data can increase significantly the understanding of the relationship between ageing and skills and can allow comparing skills across different generations. So far, evidence based on cross-sectional studies was incomplete because it did not clearly disentangle whether the effect of ageing was due to neurological evolution, to cohort or to period effects. The unique opportunity of linking PIAAC to 1994-1998 IALS data which contains comparable measures of basic cognitive skills (i.e. literacy) allows us to examine trends over time at the cohort level with the possibility of distinguishing whether there is skill gain or loss over the lifetime of individuals and over time between cohorts. As already mentioned in Chapter 1, there are 11 European countries that participated in both PIAAC and IALS, and for which it is therefore possible to study the evolution of literacy skills over time, namely BE (Fl), CZ, DE, DK, FI, IE, IT, NL, PL, SE and UK[28]. We will consider 10 of these countries in the analysis; as a matter of fact, despite participating in both surveys, DE does not provide information in PIAAC on age as a continuous variable; since this variable is fundamental for the purposes of our analysis, we therefore had to discard DE from this part of the study.

[28] While for IALS the UK includes the whole country (Great Britain+Northern Ireland), only England and Northern Ireland participated in PIAAC, so there is a discrepancy in the representation of the country in the two surveys. However, since England and Northern Ireland represent around 87% of the UK working age population, we decided to retain the country in the analysis.

3.3. The effect of ageing on skills at first glance

As a first step in investigating the effect of ageing on skills, we start by running a simple OLS regression in which the dependent variable is the individual score in literacy skills. For this first part of analysis, we use PIAAC data only. Following Green and Riddell (2013), we assume that individuals at birth are endowed with two key characteristics, i.e. ability and parental resources (which include for example, parental income or parental efforts in raising their children), which jointly determine child acquisition of literacy skills during the school time-period. We also assume that once individuals leave school, acquisition of literacy skills is likely to be more difficult.

Our main interest is in assessing whether literacy declines or rises with age. In addition we also explore the link between literacy and parental characteristics and resources, and between literacy and formal schooling, since those two are the main channels through which individuals develop their skills. Due to the type of data available, once again we will not be able to estimate causal relationships, thus what we will discuss are mainly correlations rather than pure causal impacts.

The main independent variable is age. Age can enter the regression either as continuous plus a squared term, or as categorical, dividing the population into 7 age groups (16-22; 23-29; 30-36; 37-43; 44-50; 51-57; 58-65)[29]; we therefore use two alternative specifications using one or the other. The variables we use as controls are: individual educational level categorised as low (ISCED 0-2), medium (ISCED 3-4) or high (ISCED 5 or higher), gender, and variables related to parental background. In particular, we include mother's and father's education and immigrant background. Parental education follows the same categories as above (low, medium and high); in addition we add an extra category for missing responses, that is used as baseline group. In this regression we take into account the complex survey design of PIAAC, and therefore estimate the regression for the 10 plausible values and 80 replicates weights.

Before showing the results, it is worth explaining a caveat that will hold not only for this part of our analysis, but also for the rest of the Chapter. When comparing coefficients in the regressions, e.g. to consider the effect of age (or later on, of cohort) on this score, we should always bear in mind that while interpretation is straightforward *within* each country (e.g. a higher coefficient for one age group than another one indeed implies a stronger effect of age for that group in that country), more care should be used in comparing coefficients *across* countries; since our dependent variable is the individual score in literacy skills, and the level of skills varies significantly across countries, the same coefficient (i.e. the same score decrease or increase in absolute terms) can imply a change that is very relevant in one country and only marginal in another.

Table A14 to Table A17 present the results by country and for both age specifications (continuous and categorical).

[29] This division is driven by sample sizes and data availability: a narrower division, e.g. groups of 5 years was too detailed and resulted in a collinearity problem in the estimation. The 7 years group is the narrower division allowing us to estimate all our regressions avoiding collinearity issues.

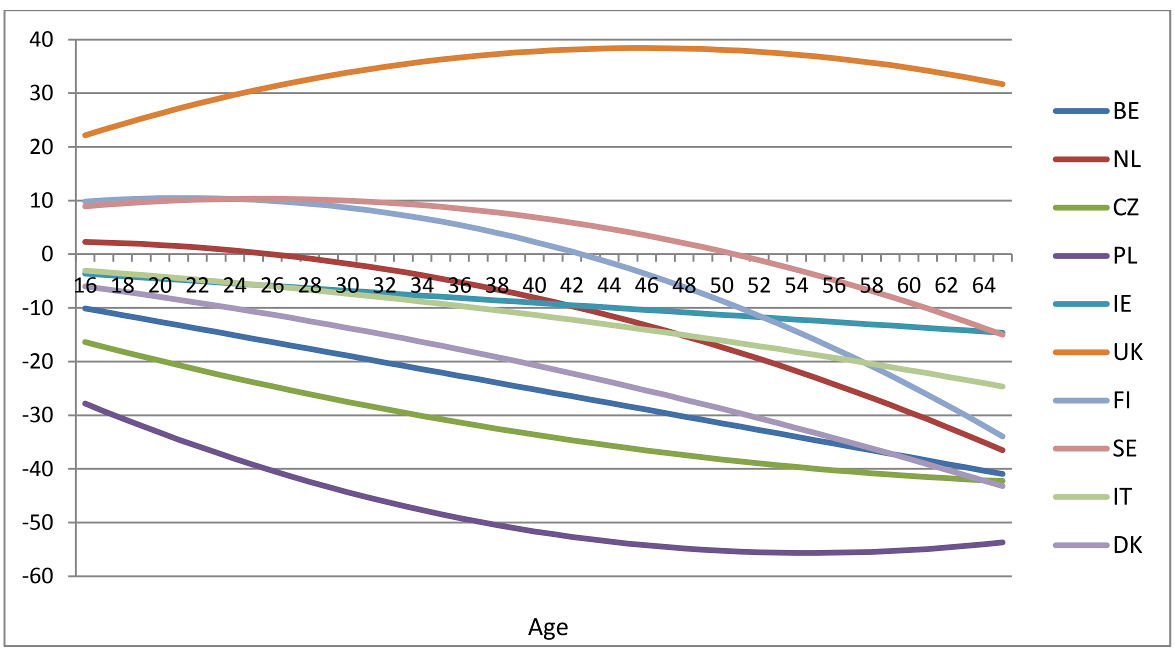
In general, we see that skills decline with age. In BE, CZ, DK, IT, NL and PL, we observe a negative age effects significant in all age groups. In FI, IE and SE the negative age effect is significant, but only for older age groups (from around 40), meaning that the decline seems to start later in these countries. In the UK on the other side, we find a positive age effects in all the age groups, compared to the first one. This may be not so much a sign of a positive effect of ageing, but rather that the youngest generations start off with lower skills, so that the ageing effect is compensated by the worse starting point of the youth. We will look into this in the rest of the Chapter.

Looking at the specification with age as continuous variable, it is more complicated to find patterns across countries, since we need to interact the two coefficients to be able to interpret the figures. However, this specification offers us a better opportunity to study the direction and the pace at which age affects skills, and whether the decrease happens at an increasing or decreasing rate. In order to better observe patterns by country, in Figure 8 we plot the estimated evolution of literacy skills by age. On the x-axis we report the years of age (ranging from 16 to 65), and on the y-axis the value resulting from the sum of the coefficients related to the age effect; the value reported is therefore calculated as

*Y = (coefficient for age) * age + (coefficient for age squared) * (age squared).*

When looking at the graph, we should bear in mind that it should not be used to compare levels of skills across countries, since the values reported do not consider all the other variables or the constant, so the levels shown are not representative of the true skill levels in the countries; the chart should be used only to compare the rates of increase or decrease in skills with age.

Figure 8: Shape of age effect on skills



Notes: Own elaborations on PIAAC data.

We observe several different patterns. For a first group of countries, namely SE, FI and NL, age has no or limited effect on the very first age groups (up to 30, 25 for NL), while it increases dramatically later on. Thus in these countries the negative age effect is driven mostly by a decline in the later stages of life, while in the first period ageing appears to have no substantial effect on skills. In a second group of countries, which includes CZ and PL, the opposite happens: the decline in skills takes place in the first years, and then skills decline, but at a diminishing rate. In BE, DK, IE and IT, on the other hand, the decline is constant over the whole age distribution; the slope of the decline is different between countries (e.g. the decrease is slower in IE than in DK), but constant within each country, i.e. the shape of the age effect resembles more a straight line than a curve. As before, in the UK we observe that surprisingly, age has a positive effect on skills, which seem to increase at least until age 45, when they start declining slowly.

As can be seen in Table A14 to Table A17, in most of the countries the control variables behave as expected: higher education is always associated to higher skills and the same holds for mother's and father's education, although this result is less consistent across countries (remember that here the excluded category is individuals who do not report any value for mother/father education). Individuals whose parents have an immigrant background usually have lower skills, with the exceptions of CZ and PL. The gender dummy behaves differently in different countries: in CZ, DK, FI, IT and UK, there seem to be no differences between males and females, while in the remaining countries males perform better than females, apart from PL where female outperform males.

So far we have seen that, on average, skills seem to decline with age; nevertheless interpreting the age coefficient in a cross section regression requires some care. As a matter of fact, the differential between two age groups could be due to a true ageing effect, but also to a cohort (or generation) effect, as discussed in the previous section. Indeed, when comparing a 35 years old to a 25 years old, we should keep in mind that the 35 years old comes from a 10 years older generation, and that differences in skills between the two individuals are probably due to a combination of the true ageing effect and cohort effect, as probably happens in the case of the UK described above. For this reason, in the following sections we go further and try to separate the ageing and cohort effects.

3.4. Disentangling ageing and cohort effects: a first step

In this section, we try to better disentangle the separate effects of ageing and cohort on individual skills.

When considering **cohort effects**, we are taking into account that generations may get better off (worse off) as time passes by. Thus, for example, if the skills of our parents' generation are lower (higher) than our generation, then we can say that there is an average skill gain (loss) in the generation (cohort) contribution to the skills of the country.

On the other hand, individuals can lose (skill loss) or improve (skill gain) their level of skills as time passes by; this is the **ageing effect**, which tries to capture the impact of getting older on the level of skills of the individual. As a matter of fact, due to neurological, behavioural and social factors, individuals can have different levels of skills at different points in time in their life.

Ideally, we would need longitudinal data, that is, a survey that follows individuals from different age cohorts throughout their lives. This type of data is not available, since neither IALS nor PIAAC include a panel component. However, as already mentioned in Chapter 1, PIAAC was specifically designed to link to IALS in the domain of literacy, so that the information on literacy skills provided by the two surveys is comparable. Since both surveys track a representative sample of the population (therefore providing an unbiased estimate of the distribution of literacy skills at that point in time), and they are implemented between 13 and 17 years apart from each other, their design allows us to build synthetic cohorts, that we can use for our analysis[30].

Since IALS was carried out at different points in time for different countries, the number of years between observations varies depending on the country. For countries where the survey took place in 1994 (i.e. IE, NL, PL and SE), the time span between IALS and PIAAC information is 17 years. For BE and the UK, where IALS was implemented in 1996, the span is 15 years. For the countries where the survey was carried out in 1996 (CZ, DK, FI, IT), the period is shorter, 13 years. Based on these time spans, we identified for each country the cohorts that we were able to observe in both surveys; for the first group of countries, we are able to track the cohorts aged between 16 and 48 in IALS (1994), who were between 33 and 65 years old in PIAAC; for the second group, we can follow cohorts aged between 16 and 50 in IALS (1996), who were aged 31 to 65 in PIAAC; for the last group, those aged between 16 to 52 in IALS (1998) correspond to those aged from 29 to 65 in PIAAC.

The results presented in this section are first raw estimates of the age and cohort effects possibly going on in the different countries. These figures do not take into account any other control variables, such as the level of education. Nevertheless, these descriptive findings can provide useful information about the current skills profiles in the different countries, and how they have evolved compared to around 15 years ago. In Section 3.5 we will follow a more rigorous approach and estimate the age and cohort effect also taking into account the effect of other disturbing factors.

Figure 9 and Figure 10 present the ageing effects, while Figure 11 and Figure 12 show the cohort effects[31]. Before results for each country are presented, it is worthwhile to discuss in some detail what the figures display.

[30] As already mentioned at the beginning of this Chapter, since for DE the only age information available in PIAAC is about 5-years age groups, we decided to discard this country from the analysis, because the information on age as a continuous variable is strictly fundamental under this setting

[31] For the cohort effect analysis, we used two-years of age intervals to increase the sample size and make estimates more reliable; however, for measuring the ageing effect, we considered the single years of age. This is because of the uneven number of years between the observations (13, 15 or 17), which made it impossible to track cohorts covering two subsequent years of age in the two surveys.

The left-hand side (or column 1) of Figure 9 and Figure 10, which are aimed at illustrating the **ageing effect**, shows a comparison between the mean scores (shown with lowess smoothing[32]) for each age cohort in IALS and in PIAAC; the age of the cohort in IALS is reported at the bottom of the chart, and the age in PIAAC 13 to 17 years later is reported at the top[33]; the red line represents average IALS scores, and the blue line represents PIAAC ones. Whenever the red line is above the blue one, average scores for the cohort represented by that point have been decreasing with age between the two surveys; when the blue line is above the red one, ageing produced a skill gain rather than a skill loss.

The right-hand side (or column 2) of Figure 9 and Figure 10 present the differences in scores and their level of significance; the former are computed as differences between PIAAC and IALS[34], where a positive value of the difference (represented by the dot) implies higher mean skills in PIAAC, and therefore a skills gain, and negative values represent a skill loss; confidence intervals are reported with the dashed lines in the charts, in order to show for which cohorts the average score in IALS is significantly different from the average score in PIAAC. If the confidence interval includes value 0 of the difference in scores, results are not significant.

The left-hand side (or column 1) of Figure 11 and Figure 12, which are aimed at illustrating the **cohort effect**, compares the mean scores (using lowess smoothing) of individuals in IALS (red line) with the mean scores of individuals of the same age in PIAAC (blue line). If the blue line is above (below) the red one, then individuals in that age group are on average more (less) skilled in PIAAC than individuals of the same age in IALS, which implies that the new cohorts are more (less) skilled than the past ones.

The right-hand side (or column 2) of Figure 11 and Figure 12 present the differences in scores and their level of significance; it therefore displays whether the difference in the average score of individuals of the same age between IALS and PIAAC is statistically different. Positive values of the difference, represented by the black dot, mean higher average skills in PIAAC, while negative values imply a skill loss across cohorts. Confidence intervals are provided (dashed lines) to test the reliability of the trends in skill loss or gain due to cohort effects. As above, if the confidence interval includes value 0 of the difference in scores, results are not significant.

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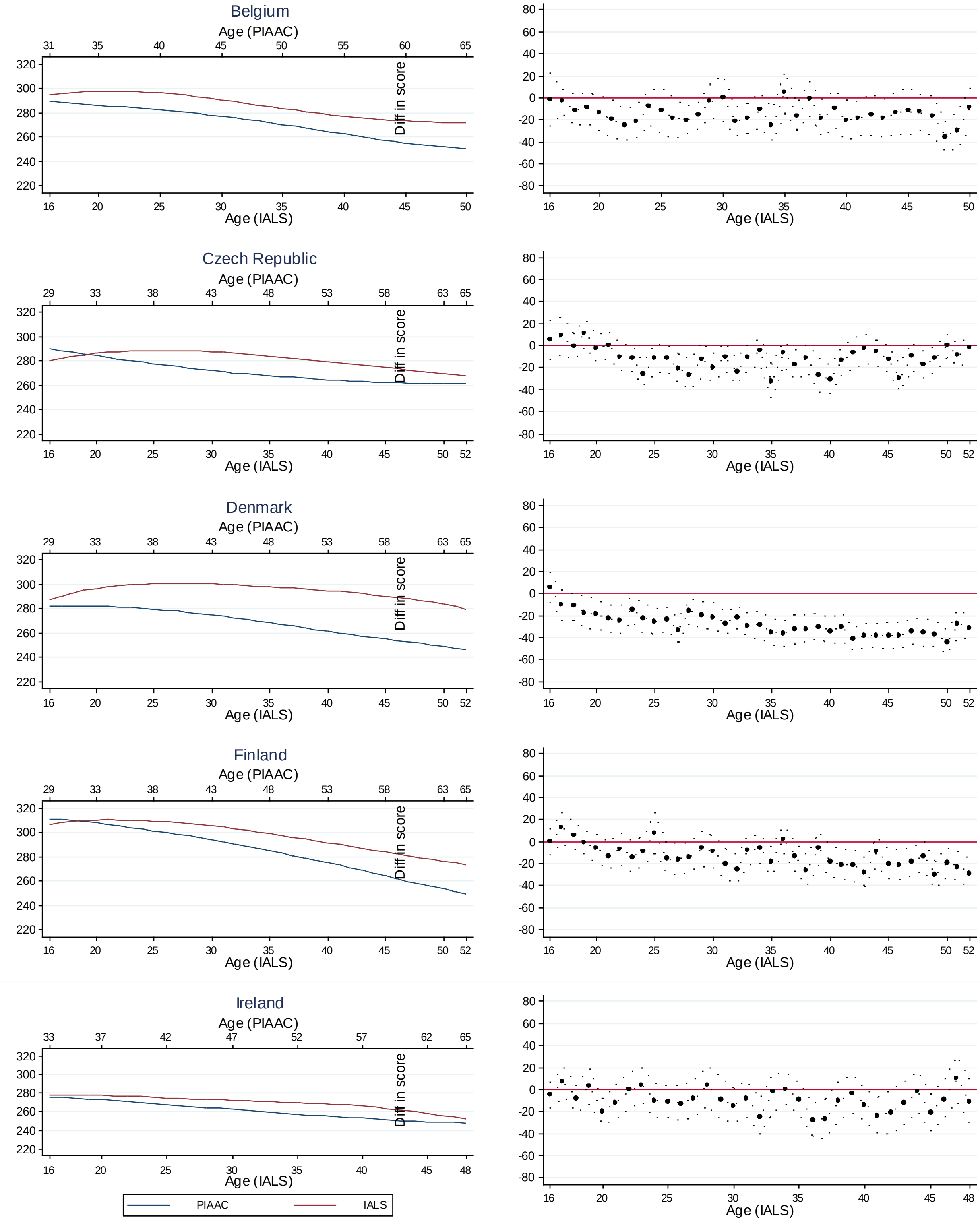
[32] LOWESS (Locally Weighted Scatterplot Smoothing) is a tool used in regression analysis that creates a smooth line through a scatter plot to help the reader see the relationship between variables; instead of seeing the actual points, lowess smoothing produces the line that better fits those points.

[33] It is worth pointing out once again that while the analysis for cohort effect can be done considering the whole sample in both surveys – i.e. all age groups, from 16 to 65 – for the ageing effect the age group we can consider is reduced because of the need to track individuals over time; as a consequence, in the analysis we are forced to discard the older age group in IALS, and the younger age group in PIAAC, as both cohorts are excluded from the population in the other survey.

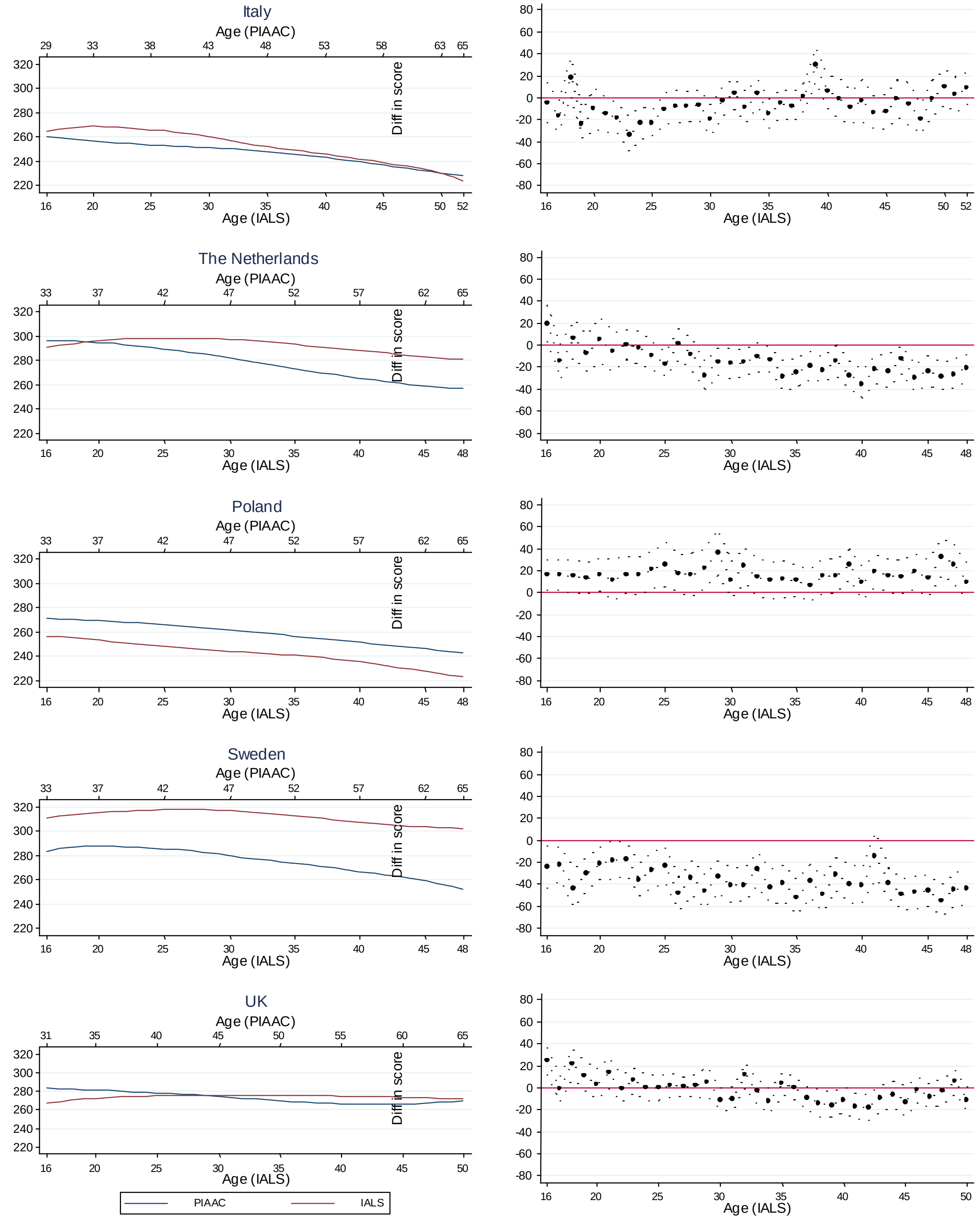
[34] For the sake of simplicity, only the age of the cohort in IALS is reported in these charts.

Figure 9. Ageing effect in BE, CZ, DK, FI and IE – Trend average scores (column 1) and differences in scores and confidence intervals (column 2)



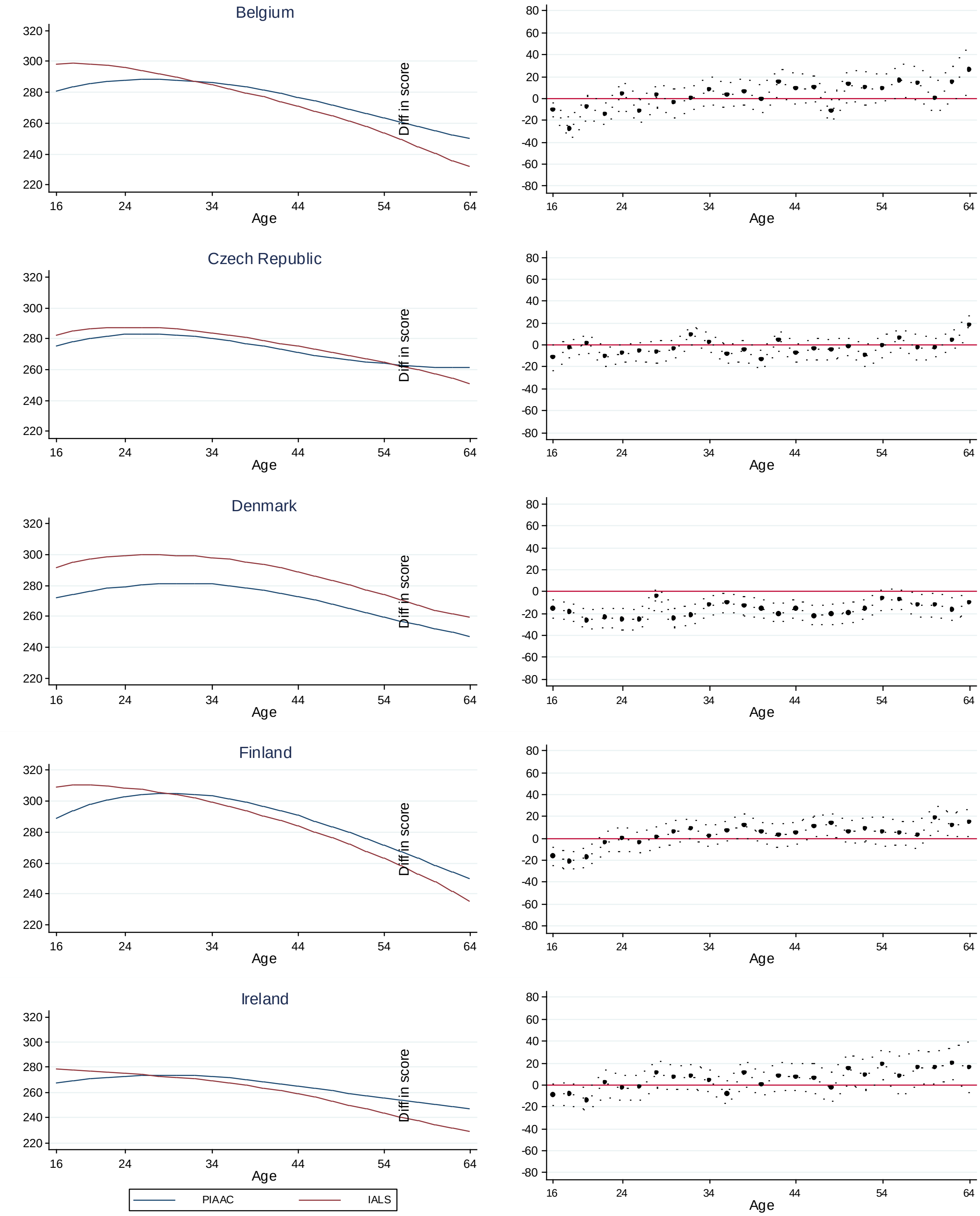
Notes: Own elaborations on IALS and PIAAC data.

Figure 10. Ageing effect in IT, NL, PL, SE and UK – Trend average scores (column 1) and differences in scores and confidence intervals (column 2)



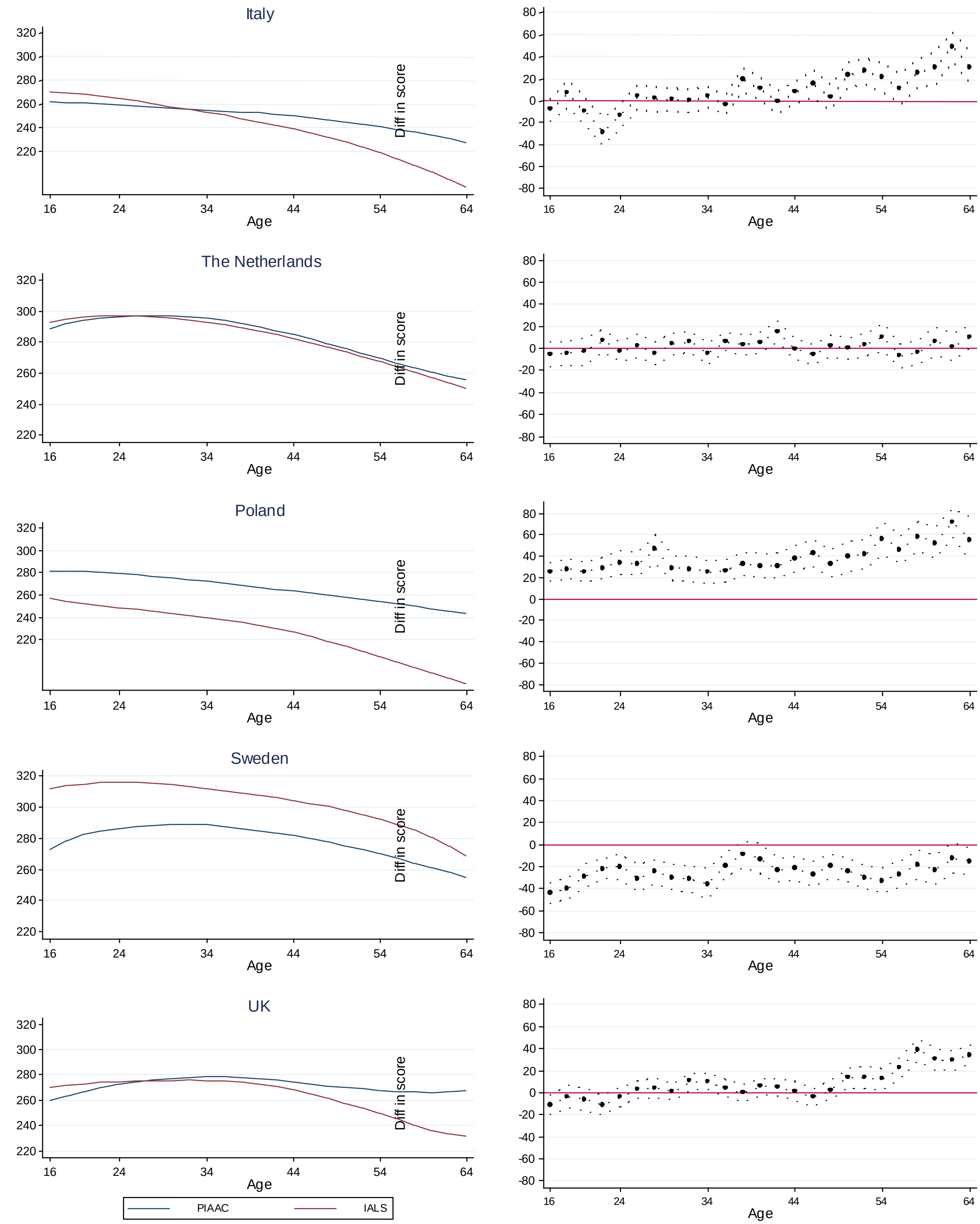
Notes: Own elaborations on IALS and PIAAC data.

Figure 11. Cohort effect in BE, CZ, DK, FI and IE – Trend average scores (column 1) and differences in scores and confidence intervals (column 2) of individuals aged 16-65 in IALS and PIAAC



Notes: Own elaborations on IALS and PIAAC data.

Figure 12. Cohort effect in IT, NL, PL, SE and UK – Trend average scores (column 1) and differences in scores and confidence intervals (column 2) of individuals aged 16-65 in IALS and PIAAC



Notes: Own elaborations on IALS and PIAAC data.

For the **ageing effect** we can identify the following patterns from Figure 9 and Figure 10:

a) In most of the countries ageing is associated to a deterioration of skills: 8 of the countries under study show a negative age effect or, better said, a skill loss associated to ageing.
b) The only exceptions are PL and the UK; for PL, all cohorts appear to have higher skills when they age, i.e. the PIAAC scores 17 years after IALS are higher than in the previous survey; for the UK, we notice a slight increase in skills for those aged between 16 and 30 in IALS, but significant only for the younger cohorts. The trend is then reversed for those aged 30 or above in IALS, although the differences are weakly significant.
c) In DK and SE the negative ageing effect is statistically significant for all the age groups considered, in NL the negative impact is significant for the cohorts aged 28 or above in IALS, while in CZ it is for most of those who were 23 or older (except for a few age groups in between); in interpreting this result, it should be considered that the youngest cohorts in IALS were likely still in the education system: the fact that they were probably still accruing additional skills can explain why the effect for the youngest cohorts is not significant, as it is possible that between IALS and PIAAC their skills were growing in the first phase, and then started declining afterwards.
d) BE, FI, IE and IT show trends that are generally not statistically significant, or at least not consistently across cohorts; in BE and IT the negative ageing effect appears to be more significant for relatively young cohorts in IALS, while in FI it is for the older cohorts.

For the **cohort effect**, as can be noticed in Figure 11 and Figure 12, again mixed results arise.

a) At one extreme, in DK and SE we find, across all age groups, a statistically significant skill loss between subsequent generations. A skill loss, or said differently, a negative cohort effect, means that younger generations possess a lower level of skills compared to the older generations, which suggests that some institutional or socio-economic factors may have been at work, lowering down the level of skills possessed by younger generations. These are the same countries for which we found a consistent negative ageing effect; this implies that not only subsequent generations are endowed with lower skills, but also that all individuals, whatever generation they belong to, see a decrease in skills as they age; if this holds also for those who are now young, this means that in the future the overall level of skills in these countries will keep decreasing.
b) At the opposite extreme, we find once again Poland, which shows, across all age groups, a statistically significant skill gain. A skill gain, or said differently, a positive cohort effect, means that the most recent generations are endowed with a higher level of skills compared to previous ones.
c) In between, we find a number of countries with mixed, or weakly significant, results:
    - In BE, FI and IT, a negative cohort effect is found for the youth (the effect being statistically significant only for some of the youngest individuals in the population), while a positive effect is registered among older age groups, weakly significant for BE and FI, and more consistent for IT starting from age 45; this means that the generation who is now (i.e. in PIAAC) young is on average less skilled than the generation that was young in IALS, while the generation who is currently old is better off than the previous one.

- In IE and UK, the only significant result is the positive effect among older age groups, stronger for the UK, while only weakly significant for IE.

d) Last, in CZ and NL no statistically significant cohort effect can be identified.

With these results in place, we now move to the next section where multivariate analysis will be undertaken so as to control for a number of socio-economic characteristics and better disentangle the age and cohort effects.

3.5. Disentangling ageing and cohort effects: a multivariate analysis

Ageing and cohort effects presented in the previous section are raw estimates that consider only skill levels, age and cohort, and gave us a first insight into the effects in place. Nevertheless, these raw estimates do not take into account other factors that we know are important in the development and formation of skills, such as the individual's level of education and parental characteristics. Given the consistent time lag between the two surveys (between 13 and 17 years); it is possible that some changes in the composition of the population took place that might affect the estimates. For example, education expansion that might have occurred in some countries: without controlling for the level of education reached by the individuals, we run the risk of misinterpreting the differences observed between different cohorts over time, attributing to cohort effects also the impact of increased tertiary education.

For this part of analysis, we pool the PIAAC and IALS samples, therefore building a synthetic cohort; this new dataset allows us to estimate the same regressions as in Section 3.3, but adding cohort dummies to the main specification. Given the similarities in the results obtained using age as continuous or as categorical variable, in this section we focus on the specification using age categories only. The cohort dummies will take the same value for individuals born in the same year range, independently of the survey.

When trying to disentangle age, cohort and year effects, an identification issue arises, since the year is basically the sum of birth year and age. Thus, an assumption we have to make before estimating the regression is that there is no year effect, i.e. there is no such a thing that increases or decreases skills in all groups defined by age and cohort in a similar way in a given year.[35] This is an assumption usually made in the literature (see Green and Riddel, 2013).Given this assumption, we can identify age and cohort effects. Unfortunately, since we have only two cohorts per country, it is not possible to interact age and cohort, so to allow for the ageing to have a different effect for the different cohorts.

We consider the whole sample in PIAAC and IALS, ranging from age 16 to age 65. As in Section 3.3, we build 7 age groups (16-22, 23-29, 30-36, 34-43, 44-50, 51-58, 58-65); we then create 7 cohort groups: the first cohort is the oldest one, and it is composed by individuals who are 51-65 in IALS, and have no correspondence in PIAAC; the second cohort by individuals who are 44-50 in IALS and 57-63 in PIAAC – or 59-65/61-65, according to the time lag between the two surveys[36]; the last cohort is the youngest one, and it is composed by individuals who are 16-28 – or 16-30 or 16-32, depending on the time lag - in PIAAC and have no counterpart in IALS. In Table A18 we present the age groups in IALS with the corresponding cohorts in IALS and PIAAC; cells highlighted with the same colour represent individuals included in the same cohort across the two surveys. As for the control variables in the regressions (not reported in the regression tables in this and in the following Sections), they are the same as the ones

[35] A violation of this assumption would be that in a given year between IALS and PIAAC, e.g. in year 1999, the skills of the overall population increased similarly in all age and cohort groups due to external events (e.g. natural disasters or reforms). In our case, we have no evidence of what event could lead to such an increase/decrease, so we assume no year effect.

[36] The time lag between PIAAC and IALS is 13, 15 or 17, depending on the year when IALS took place in the country; we therefore adjust the cohort composition accordingly.

proposed in the age regression in Section 3.4: level of education, parental level of education, migrant status and gender. The reference categories for age and cohort are respectively the youngest age group (16-22) and the oldest cohort (aged 51-65 in IALS). The regressions are estimated separately by country[37].

Table A19 presents the results: in general we notice that the true ageing effect is much larger than the one estimated with the PIAAC sample only. In all the countries, once we take into account the cohort effect, the coefficients associated to the age groups are larger than the one estimated in section 3.3. For IE, FI and SE, also the coefficients that were not significant in the previous specification – i.e. those relative to the relatively younger age groups – are now relevant; for the UK, what appeared to be a positive ageing effect now turns into a negative one. In most of the countries, the coefficients increase as age increases, suggesting that the decrease in skills continues over the life span of the individuals. IT and PL are two exceptions, since in PL the ageing effect is negative in all age groups, but coefficient are very similar between themselves, especially in age groups between 30 and 57, suggesting that the overall population has lower skills than the very young age group, but the progressive age effect is less pronounced; in IT instead there is a negative age effect that does not increase proportionally with age, but depends on the age group.

If we look at cohort effects an interesting pattern emerges: in most of the countries more recent generations are performing worse than the older ones, indeed the coefficients associated to younger cohorts are negative and significant, meaning that they have lower skills that the reference cohort (individuals aged more than 50 in IALS), but in some other countries we see either no cohort effect or even a positive cohort effect.

More in detail, we see that in some countries there is a strong negative cohort effect, increasing as cohorts become younger, meaning that more recent cohorts have fewer skills than older cohorts. This is the case in BE, CZ, DK, NL and SE, even though in NL the coefficients are smaller than in the other countries, meaning that the decrease is less pronounced. In IE and the UK, there is a negative cohort effect only from cohort 5 onwards: only very young generations (those who were aged under 30 in IALS) have lower skills than the older ones, while middle cohorts still perform in line with the previous generations. Interestingly, in FI there is no cohort effect[38], while in IT and PL we see a positive impact for all more recent generations, implying that they have a higher level of skills than the reference generation; however, coefficients follow a reverse u-shape: skills seem to be increasing up until cohort 4, are quite similar for cohorts 4 and 5, and then decrease for the last generations, meaning that all cohorts have higher skills than the first one, with the highest improvement taking place for middle cohorts, while the most recent ones still have higher skills than the first one, but lower than the middle ones.

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[37] Given the combination of PIAAC and IALS we could not use the replicated weights, since in IALS there are only 30 replicated weights, while in PIAAC there are 80. Nevertheless we could use the 10 plausible values, since IALS test scores have been adapted in order to match the PIAAC plausible values.

[38] The only significant coefficient refers to cohort 7, i.e. individuals that were in PIAAC, but too young to be captured in IALS. For this reason, despite including this group in the analysis, we prefer not to place too much emphasis on the relative coefficients.

Thus, the negative cohort effect found for most of the countries helps explaining why the true ageing effect is larger than the one estimated using PIAAC data only. Without considering the cohort effect, which suggests that younger cohorts start off with lower skills than the older cohorts, the ageing effect that we found was smaller (or even had a different sign) simply because the current difference between the skills of old and young generation is small. But this difference is small not because older individuals were able to preserve their skills over time, but because the young individuals started off with lower skills, thus having a lower level of skills than that the older individuals had at their same age.

A comparison between the results that emerged from Table A14 to Table A17 and those from Table A19, taking also into account the figures presented in the previous Section, provides some interesting examples of how what appear to be ageing effect at a first sight can indeed hide different patterns of ageing and cohort impacts.

Let’s consider DK first. Table A14 showed what appeared to be a strong negative effect of ageing on skills. Figure 9 also provided evidence of a negative ageing effect; however, Figure 11 also showed the presence of a significant negative cohort effect. Table 4 helps us clarify that the negative cohort effect – that suggests that more recent generations are worse off in terms of skills than the previous ones – was partially compensating the impact of ageing, which, as shown by Table A14 is actually stronger than it seemed.

Another interesting case is UK. Table A17 showed a positive ageing effect for the country; the figures in the previous Section showed only weak ageing effects and a rather strong positive cohort one for older age groups, meaning that the older group in PIAAC seems to be better off than the older group in IALS. Table A19, which also controls for other socio-demographic characteristics of the individual, suggests that the positive ageing effect of Table A17 is actually hiding a negative ageing effect, compensated by a negative cohort effect (with more recent generations being worse off than the previous ones).

These patterns lead to some implications: countries where younger cohorts are performing worse than the older cohort ring the bell to the performance of the educational system. Are the new generations less prepared than the older ones? If this is the case it is worrying, since we have seen that skills tend to decrease with age, and the fact that younger cohorts start off with lower level of skills indirectly implies that the overall population will hold lower and lower skills as time goes by. On the other side, fewer concerns are raised by countries where there are no differences between younger and older cohorts, even if the ideal situation would be to increase the skills of the younger cohorts, as it happened in IT and PL. Moreover, even these two countries are not entirely exempt from a critical judgment. Are the new generations more skilled simply because there are more people enrolled in higher level of education? While this would in any case be a positive outcome, proving that education expansion is a successful policy, it would nevertheless be desirable that new generations have higher skills even at the same educational level. This question cannot be answered with the current regressions, since, despite controlling for education, we are not allowing ageing/cohort effect to vary by educational level. Finally, in light of the evidence provided in Chapter 1, it is also necessary to consider how literacy skills evolved, and the role of ageing and cohort effects, at different points of the skill distribution, i.e. taking into account low and high achievers. We therefore proceed further in the analysis in two ways: first we run the same regressions adopting a quantile approach, studying cohort and ageing effects on the different quantiles of the skill distribution; second we replicate the OLS and the quantile regression by level of education, to assess whether skills loss/gain in the new generations is consistent across education groups.

3.6. Ageing and cohort effects over the skills distribution: a quantile regression

In addition to the OLS regression we run a series of quantile regressions to investigate whether the cohort and ageing effects affect differently different quantiles of the skill distribution.

A brief definition of quantiles can be that an individual scores at the τ^{th} quantile of the distribution of skills if he performs better than the proportion τ of the reference population and worse than the proportion $(1-\tau)$. So for example, half of the population performs better than the 50^{th} quantile (the median) and the other half performs worse.

Quantile regression has a link with the ordinary least square regression: while the OLS results in estimates that approximate the conditional mean of the response variable given certain values of the predictor variables, quantile regression aims at estimating either the conditional median or other quantiles of the response variable. The interpretation of the coefficients resulting from a quantile regression is basically the same as the interpretation of the OLS, applied to the quantile of interest. A quantile regression could be estimated for all the 99 quantiles of a distribution, but we simply focus on three important quantiles, i.e. 10^{th}, 50^{th} and 90^{th}. The 10^{th} quantile focuses on the bottom part of the skill distribution, thus on what we can consider as ***low achievers*** within a country, and estimates resulting from this regression will provide some insight into the ageing and cohort effect in this particular group of individuals. On the other side, the 90^{th} quantile focuses on the top part of the distribution, thus on ***high achievers*** within the country.[39] Finally, studying the median it interesting to see effects on the middle part of the distribution and how they diverge from the mean (estimated in the OLS) and by the extreme quantiles.

In the first three columns of Table A24 to Table A33 we report the estimates for the 10^{th}, 50^{th} and 90^{th} quantiles by country for the whole population. We focus in this section on the first three columns of each table, presenting the estimates for the overall population (the other columns will be discussed in the following section since they refer to estimates done by level of education).

Again different patterns emerge in different countries, both for age and cohort effect.

[39] Notice that the concept of high and low achievers used here is not directly connected with skill level. We use high and low achievers to refer to the bottom and top part of the skill distribution within a country.

As for ageing effect, we see that in all the countries the effect is negative in most of the quantiles, nevertheless there are some differences across countries: in IE and SE the negative ageing effect is larger at top quantiles, meaning that the high achievers part of the skill distribution loses more skills than the low achievers as age increases. On the other side, in BE, CZ, DK, FI and NL we observe the opposite: the age effect is larger at bottom quantiles, meaning that the decrease in skills due to ageing is larger in the low achievers part of the population, while high achievers manage to better preserve their skills. In both cases the coefficients increase as age increase, suggesting that that as time goes by the loss in skill is larger.

In IT and the UK we see that there is no ageing effect for the low achievers (i.e. for the 10^{th} quantile), while there is a significant negative ageing effect in the 50^{th} and 90^{th} quantiles, slightly larger in the latter. In IT, coefficients for the different age groups are very close to each other within each quantile: after a first decrease registered for the age group 23-29, skills do not appear to systematically decrease with age, at least until the second drop found for the age group 58-65. In the UK, on the other hand, the negative effect increases with age, but coefficients for the 50^{th} and 90^{th} quantiles are basically the same.

In Poland coefficient are always negative and significant in all quantiles, but very similar across quantiles and between age groups. This suggests that the negative effect of age on skills is similar across the overall distribution – although a bit weaker among the high achievers.

As far as cohort effects are concerned, again some differences between countries and across quantiles arise.

In CZ, SE, DK and NL – as already mentioned – we observe a negative cohort effect, with younger generations owning lower levels of skills compared to the older ones. In SE the negative cohort effect is in all quantiles increasing as cohort increases, and the negative effect is larger at top quantiles, suggesting that the younger generations have lower skills than the old ones, especially among the high achievers. In the other three countries, on the other side, the negative cohort effect is in all quantiles, increasing as cohort increases, but the effect is larger at bottom quantiles, implying that the more recent generations have lower skills than the old ones, and this effect is larger for low achievers.

In IE, BE and the UK, on the contrary, the negative cohort effect applies more to the higher part of the distribution. No cohort effect is observed in the 10^{th} quantile; in the middle part of the distribution, i.e. at the median level, no effect is found for IE, and the negative cohort effect for BE and UK is significant only from cohorts 4 or 5 onwards. For these countries, the only consistent result is for the 90^{th} quantile, with a negative cohort effect that increases as cohort increases. This suggests that there has been no deterioration in skills for the new generations in the low achievers part of the population, while a slightly decrease in the top part of the distribution took place. In FI there is no cohort effect in any of the quantiles.

In IT, we observe that the positive cohort effect that we found in Table A19 is mainly driven by the bottom part of the distribution. We find a positive cohort effect at the 10^{th} quantile, increasing as cohort increases, implying that younger generations start off with higher skills that the old ones; on the other hand, the positive cohort effect observed at the 50th quantile is similar across all cohorts when compared to the baseline, with the coefficients for cohorts 2 to 7 being not statistically different from each other; finally, no cohort effect emerges at the 90th quantile. Thus, younger cohorts of individuals located in the middle and top part of the distribution did not improve nor worsen their level of skills, compared to the previous generation, while younger cohorts of individuals located at the bottom of the skill distribution, i.e. the low achievers, have higher skills than the older generations.

In PL we see what appears to be a positive cohort effect at all quantiles; however, cohort coefficients are similar within each quantile, suggesting that the improvement is only relative to the very old cohort, while subsequent ones have relatively stable levels of skills. Coefficients are larger at the bottom of the distribution, meaning that the greater improvement comes from the low achievers.

This part of the analysis showed how the overall ageing and cohort effects can be driven by individuals at different points of the skills distribution depending on the country. However, it is also possible that these patterns vary depending on the level of formal education of the individuals; in the next Section we try to take this issue into account.

3.7. Drivers of skills change over the skills distribution: the effect of education

In order to assess whether different patterns emerge across different educational groups, in this section we carry out the same type of analysis presented in Section 3.5 and 3.6, i.e. the OLS and quantile regressions for the estimation of ageing and cohort effect, by level of education. For sample size issues, we consider here two possible levels, high versus medium-low. We focus on this division since we are mainly interested in seeing differences in skills' preservation/deterioration distinguishing between university graduates and individuals with at most upper secondary education. For this reason we group together all individuals who do not have a tertiary degree, independently of whether they reached upper secondary education. Since it is reasonable to assume that completion of higher education occurs after being twenty years old, for regressions concerning those with high education we drop the group of individuals aged 16-22 and consider as reference age group those aged 23-29.

We present the results from OLS regressions in Table A20 (high education) and Table A21 (medium-low education); estimates from quantile regressions are provided in Table A24 to Table A33 (columns 4-6 for high level, columns 7-9 for medium-low).

The OLS estimates presented in Table A20 show that the age effect is often stronger among those with medium-low education than among the highly educated. In BE, CZ, DK, IE and SE, the effect is significant across all age groups (with the exception of the first one, for which evidence is weaker for some countries) for both educational levels, increasing as age increases. For FI and NL, among the highly educated the effect is significantly negative only for the 2 older age groups of individuals, while the negative ageing effect is consistent for all age groups among those with medium-low educated; this suggests that highly educated people manage to maintain their skills longer and ageing has a negative effect only from 50 years of age onwards. In IT, we find a similar pattern for the highly educated, while in the other group the negative effect is concentrated in the young and old age groups. In the UK, we find for both high and medium-low educated individuals a negative ageing effect that is significant only for the three oldest age groups[40].

Broadly speaking, when considering both the effect of education and of the distribution of skills on the ageing effect, we can divide the countries in three main groups:

- A first group includes countries for which individuals at the top of the skills distribution are less prone to ageing, and for which higher education also produces the same effect. This group includes BE, DK, FI and NL; for BE and NL, the positive effect of education is limited to the young age groups; for BE, being at the top of the skills distribution gives an advantage for ageing only for those with high education.
- A second group includes countries for which a higher level of education reduces the negative effect of ageing, but for which no difference arises depending on where along the skills distribution the individual is placed; for these countries – namely CZ, IT and SE – either there is no significant difference in age group coefficients across quantiles, or higher skills are associated to a worse ageing effect over the lifetime.
- Finally, in IE and UK, no positive effect of education on the ageing process is found.

Among the highly educated, we find no age effect in PL, neither in the OLS nor in any of the quantiles, meaning that in this country, individuals with high education do not deteriorate their skills with age. Similarly in IT, UK, FI and partially BE we observe a negative age effect only from 50 years old onwards, in UK and IT coming from a deterioration of skills in the middle part of the distribution and in FI and BE also among low achievers. In IE and NL the decrease with age starts earlier (from age 40), but in IE is grater in top quantiles, while in NL in bottom quantiles.

In CZ, DK and SE instead we see a negative effect basically in age groups, in the first two countries driven mostly by bottom quantiles, while in SE by top quantiles.

Among those with medium-low education, in CZ, BE and SE the negative age effect is similar across different quantiles, so with age, across the overall distribution, skills decrease by a similar magnitude. In IE and UK the negative effect is larger at top quantiles, and basically not significant at the 10th quantile, thus in IE only the smarter individuals (among the medium-low educated) are losing their skills with age.

[40] As a robustness check, we carry out the same analysis considering low and medium education separately. Results are reported in Table A22 and Table A23. What emerges is that overall, individuals with medium and low education show similar ageing effect trends, stronger than those for the highly educated, therefore confirming the results we find in Table A21. In CZ, the ageing effect for the medium/low education group appears to be stronger for the low educated, but nevertheless different from that for the highly educated. For FI, IT and PL, it seems that the overall result is driven by those with medium education. Only for the UK the effects found in the group with medium education resemble more the ones found for the highly educated.

A similar pattern in observed in DK, FI and the NL, where the effect is negative in all quantiles but larger at the bottom one. On the other side, in BE the higher effect is found at the top of the distribution

In IT we find a negative age effect at the 90th quantile, but some positive age effect at the 10th; finally, in PL the age effect is very small, and affecting mostly the middle part of the distribution.

As for cohort effect among highly educated people, we notice that in BE, CZ, FI, IT and NL there is no cohort effect, thus in these countries, tertiary educated younger cohorts start off with the same level of skills as the very old tertiary educated cohort, and this holds for all the quantiles of the skills distribution. On the other side, in DK, IE, SE and UK we observe the opposite: there is a negative cohort effect, increasing as cohorts get more recent. In SE and IE these negative effects are larger at top quantiles, while in DK and the UK they are similar across quantiles.

In PL instead we observe a positive cohort effect, which is driven mostly by medium and top quantiles, meaning that younger generation with high education start off with higher skills than the older generation, especially among the individuals located in lower part of the skill distribution.

It is interesting to notice that very different cohort effect patterns emerge among the population with medium-low education. As can be noticed from the OLS regressions, in CZ, SE and DK there is a negative cohort effect; in PL, IT, FI, the UK and partially in IE and a positive cohort effect; finally in NL there is basically no cohort effect. In BE the effect is mixed, with a weak positive effect at the 10th quantile, and negative at the 50th and 90th.

Again heterogeneity exists when we look at quantile regressions. In the countries where we observed a negative cohort effect, we see that in CZ the effect is similar at all quantiles, in SE the effect is much larger at top ones, while in DK the effect is larger at the bottom.

In PL we see a positive cohort effect in all quantiles, larger at the bottom of the distribution; similarly, in FI the effect is larger at the bottom quantile, but significant only up to cohort 4. In IE we observe a positive cohort effect at the 10th and 50th quantile (stronger for the former, significant only for the first cohorts for the latter), but a negative one for the last cohorts at the 90th. In IT the positive effect is only at the 10th and 50th quantiles (the magnitude being much higher at the bottom of the distribution), and no effect is found in the top part of the distribution. Finally in the UK, the positive cohort effect is found only at the bottom quantile, while some negative effect at higher ones emerges for the most recent cohort.

In the NL, as with the OLS we basically find no effect.

3.8. A reflection on the role of lifelong learning in limiting the ageing effect on skills

In the previous Sections of this Chapter, we have shown that a substantial negative effect of age on skills affects all European countries: the older the individuals, the lower their skills. As seen, skills obsolescence is a big concern in terms of policy, because of the negative consequences it can produce both at the individual level (job insecurity, risk of lower labour market participation of older workers) and at the level of the whole economic system (overall decrease in productivity). The literature has highlighted that lifelong learning[41] may have a positive role in mitigating the deterioration of skills over the life span of individuals (see Section 3.2): if formal or non-formal learning is well functioning, it could help workers to acquire new skills, therefore compensating for the loss of skills occurring with ageing. Thus it would be interesting to investigate in empirical terms if this positive relationship is also observable in our data. Nevertheless, investigating the relationship between participation in lifelong learning and individuals' skills is quite complicated. Indeed, we observe (Vera-Toscano, E. and Meroni, E.C., 2014) that participation in lifelong learning is associated with higher skills (both at the individual and aggregate level); however, the direction of the relationship is far from being clear: do individuals have higher skills because they underwent some form of training, or is this association the result of self-selection mechanisms, by which the most skilled individuals tend to participate more in lifelong learning activities? It is very well possible that both relationships are true, so it is really hard to disentangle the true effect of participating in lifelong learning activities on skills.

Nevertheless, we investigated several possibilities to at least partially discuss this issue in light of the skills formation/preservation process and in light of the employability process, although facing several limitations due to the type of data available.

The ideal setting to study the true effect of participation in lifelong learning on skills would be to observe the same individual over time, and to have a repeated measure of skills before and after participation in lifelong learning, as in the work done by Allen and Grip (2007) using Dutch panel data[42]. Given the data we are working on, it is not possible to have both the longitudinal dimension and the skill measure component, so we will again rely on PIAAC cross-sectional data.

Despite facing these limitations in data availability we are still able to try to link participation in lifelong learning activities and the development of skills. In particular, we hypothesize that lifelong learning can play a role in mitigating the negative effect of ageing observed in most of the countries[43].

[41] In this paragraph we talk about lifelong learning in general, including both formal and non-formal learning, and we refer to it using several terms: lifelong learning, learning activities, training activities. When we describe the analysis, we will explain in details which measure of lifelong learning we will use.

[42] Their main findings are that participation in training does not prevent deterioration of skills, but that skills obsolescence does not affect the risk of losing employment.

[43] With respect to cohort effect, participation in lifelong learning cannot be considered a determining factor, since cohort effects systematically refer to a whole cohort and can be mainly traced back to differences in the educational system, not to differences occurring over the lifetime of the individuals (like lifelong learning participation).

In PIAAC participation to lifelong learning is measured as any activities attended over the 12 months preceding the survey.

Therefore, our main interest lays in understanding whether the ageing process acts differently on skills for individuals who received training and for individuals who did not receive any. To study this relationship, we start from our basic model, adding to the regression a dummy variable capturing participation in lifelong learning and the interaction of this dummy with the different age groups. If the interactions included in the regression are significantly different from 0, it means that the ageing process affects differently the skills of individuals participating in lifelong learning; negative coefficients would imply that lifelong learning might indeed by slowing down the skills obsolescence process.

Before going into the results, it is worth devoting some time to the measure of lifelong learning we can use. In particular, since we are using both PIAAC and IALS, we need to find a measure that exists in both surveys, and that captures the same type of activity. We therefore decided to rely on a variable that identifies participation in both formal and non-formal education, for any reason (both job-related and personal interest), in the 12 months preceding the survey. In order to exclude those still enrolled in full time (regular) education, we focused on the population aged 25 or above. In Table A34 in the Appendix we report the coefficients associated to the estimates of the age and cohort OLS regression, including the dummy for participating in lifelong learning and the interaction of this dummy with the age groups.

Two main results arise: first, the dummy for participation in lifelong learning is always positive and significant, meaning that there exists a positive association between lifelong learning and skills: individuals participating in lifelong learning have higher skills than those not participating; once again, for the reasons explained above, we can only talk about correlation, and not about a causal effect. Second, none of the interactions are significant, implying that there is no differential age effect for individuals participating or not in learning activities: the slope of the curve for the ageing effect is the same for individuals participating in lifelong learning and for individuals not participating, meaning that both groups are subject to skill loss due to the ageing effect, irrespective of their participation in lifelong learning. These results are coherent across all countries and confirm that, while individuals who participated in lifelong learning have higher skills than the ones who did not participate, we cannot say that lifelong learning has an attenuation effect on the skill obsolesce phenomenon: individuals who participated in lifelong learning in the past 12 months are losing their skills due to age exactly as individuals who did not participate.

Our results are in line with the existing literature: participation in lifelong learning is associated to higher skills, but this is not necessary an effect of lifelong learning increasing (or preserving) skills, it could also be due to the fact that individuals with higher skills tend to participate more in training activities, and thus the mitigating effect of lifelong learning on the deterioration of skills cannot be assessed.

3.9. Conclusions

As mentioned in the introduction to this chapter, several drivers of change, affecting the distribution of skill during the lifetime of an individual, can be identified. However, due to a) limited availability of data; b) difficulties in the measurement of some features (as an example, the wealth of social relationships); c) but also due to the wide recognition enjoyed in literature, this Chapter focused on two of the main relevant factors affecting changes in the skill level of the population through time: age and cohort effect.

Several empirical studies highlighted that a general tendency to skill deterioration associated with increasing age is observable in most of western countries: when comparing skill level of individuals with different age, older individuals tend to perform worse than younger individuals, with few exceptions. However, what at first sight may appear as a consequence of the ageing process has been disentangled as the result of two different phenomena: the age and the cohort effect.

This distinction is significant in terms of policy implications: whether the process of deterioration of skills in a society occurs through the lifetime of an individual or rather across different generations does make a difference and raises the flag for targeted interventions at policy level. Knowing the source of skill deterioration is the fundamental first step for designing specific measures able to effectively contrast the problem.

Thus, in order to investigate whether and to what extent the skill of individuals living in the European countries considered in this study may be affected by age and cohort effect, we carried on a series of empirical analysis on a pooled sample of individuals aged 16-65 from the IALS and PIAAC datasets. We first provided some descriptive statistics (Section 3.4) and regression analysis on age and cohort effect separately by country (Section 3.5), then we further enriched the model by taking into consideration the original level of skill of individuals (divided in bottom, medium, top according to the distribution of skills), in order to better investigate whether some specific groups are affected more than others by age or cohort effect (Section 3.6). Finally, the model has been integrated by taking into consideration the formal qualification attained (Section 3.7). These analyses also allow us to address the issue of low performers, testing whether the process of ageing and cohort impact differently (negative/positive) and with different magnitude on specific groups (i.e. individuals with low/medium level of education and low performances).

The findings of the empirical analysis for the age effect are summarized in the Table 13:

a) A general trend of deterioration of skill with age has been observed in all European countries included in this study: as the age increases the level of skills decreases. The age effect hits differently individuals according to their level of education, original level of skills (bottom, medium, top quantile) and to the country of residence, nevertheless it is a common feature of all countries. This finding claims for the need of policies specifically oriented to prevent skill loss after the end of formal education, or to different points in time: as shown in Figure 8, the shape of the curve differs quite widely among countries, with some countries, as UK and SE, where the deterioration of skills starts later in age and some other, as IT or BE where the deterioration is increasing linearly through time (flat curve). However, although literature has highlighted that lifelong learning (together with the occupational sector and social and physical activity) can contribute preventing the skill loss, it is interesting to note that the phenomenon of skill loss affects all countries, even those where adult participation in lifelong learning is widespread (i.e. in DK, FI and NL where it is about 65%, see Goglio and Meroni, 2014). Moreover as shown by the last section of this chapter we have seen that although participation to lifelong learning is associated with higher skills, it is not associated to a softening of the skill deterioration due to age.

b) Looking more in details, we can further differentiate the findings according to which groups are mostly affected. As an example, countries placed in the last three columns of Table 13 are in an alarming situation, since it shows that in these countries individuals with low-medium levels of education (and thus already disadvantaged in terms of employment opportunities, as investigated in chapter 2) further worsen their set of skill while getting older, hence, even worsening their original disadvantage. The most worrisome scenario is the one represented by the last column of Table 13: these individuals have originally the lowest level of skills compared to the rest of the population in their country and are those deteriorating even further the already low initial level.

   In addition, this phenomenon has also effects in terms of distribution of skills: among those with low-medium qualifications, in DK, FI, NL those who are at the bottom increase the gap with those at the top of the distribution, worsening their chances;

c) Countries highlighted in light orange represent the case of individuals with tertiary attainment suffering a negative age effect: however, in the case of SE and IE it is the "smartest" portion of individuals with higher education deteriorating their skill, compared to their fellow with low or medium skill. This is an important finding because it implies that most skilled individuals tend to deteriorate their (good) level of skill more than low or medium performers.

   In terms of distribution of skills it implies that, with age, the gap between the bottom and top of the distribution shrinks; however, this is due to the lowering down the performances of the best skilled, which *per se* is not a positive outcome for the general society.

Table 13. Summary of the empirical analysis: Age effect

<table>
<tr><th colspan="12">AGE EFFECT</th></tr>
<tr><th colspan="6">positive</th><th colspan="6">negative</th></tr>
<tr><th colspan="3">higher education</th><th colspan="3">low-medium education</th><th colspan="3">higher education</th><th colspan="3">low-medium education</th></tr>
<tr><th>top</th><th>medium</th><th>bottom</th><th>top</th><th>medium</th><th>bottom</th><th>top</th><th>medium</th><th>bottom</th><th>top</th><th>medium</th><th>bottom</th></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td>IT</td><td>SE</td><td>UK</td><td>DK</td><td>IT</td><td>PL</td><td>DK</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>IE</td><td>IT</td><td>CZ</td><td colspan="3">CZ</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>BE</td><td colspan="3">BE</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>FI</td><td colspan="3">SE</td></tr>
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<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>UK</td><td></td><td>NL</td></tr>
</table>

Findings for the cohort effect are summarized in Table 14 and suggest some important considerations:

Unlike the age effect, the cohort effect particularly impact on some countries and on some specific groups: in this case sharp differences emerge among countries. If the level of skill of different generations varies within the same country it seems reasonable to hypothesize that some structural changes could be detected behind the cohort effect. More in details:

a) The worst scenario is represented by those on the right side of the table: in these countries younger cohorts have lower skill than their older counterparts. This implies that in DK and SE all young cohorts, irrespective of the qualification attained, are worse off than older cohorts; in UK and IE the problem seems to be limited to individuals with higher education qualifications only, while in CZ it involves individuals with lower and upper secondary qualifications.

   The loss of skill between generations is a big concern in terms of policy: first, given the high positive returns at individual and societal level associated to the investment in education, if young generations perform worse than the older ones it may result in a loss of competitiveness and well-being in broader terms for the whole society. This is particularly relevant if we consider that younger cohorts have to face a more competitive labour market requiring higher level of skills in information and communication technology due to the higher proportion of automatized process and the increasing technological complexity which involves all occupational sectors, even low skilled occupations.

   Second, as mentioned before, these results raise the flag for some structural changes which negatively influenced the process of skill acquisition by younger cohorts and some concerns associated to the whole quality or efficacy of the educational system may arise. In fact, although a direct measure for the quality of the system is not available in our data and the analysis performed cannot clearly define which factor determined the deterioration of skill in younger cohorts, the comparison by level of education points to the fact that some intervening factor played a role in worsening the overall performance of the educational system across birth cohorts. Indeed, if we link these findings to PISA data, which assess the skill owned by pupils 15 years old, we can show that some structural changes in the quality or at least in the performance of the educational system occurred.

b) On the opposite end there are countries showing an improvement across cohorts, which however only involves low and medium qualifications: in IT, PL, IE, FI and UK low and medium performers of the younger cohorts show higher skills compared to their older counterparts. This undoubtedly represents a positive outcome, especially because it involves the most disadvantaged segment of population, at least in terms of occupational chances (see again findings of Chapter 2).

   However, in this case the initial level of skills has to be considered as well, since if the original level of skill is low -although improving- it can still remain low compared to other countries. Indeed, improvements and deterioration have to be considered in relative terms: an improvement *per se* may not always be a sign of good performance of the system: the starting level of skill of the country is equally important. Indeed, the improvement registered in a country can still mean an overall lower level of skill if compared to another country with higher starting level which, maybe did not improve since there was no longer room for improvement (as for example in FI, which already had high levels of completion of upper secondary and tertiary education). As an example, we can hypothesize that in PL and IT the starting level of older cohort was so low that, thanks to an increase in the participation to education, increased the skill level of younger generations. As a matter of fact, OECD data show that in IT the completion of upper secondary school increased by 30% for younger cohorts (25-34 years old) compared to old cohorts (55-64 years old). Similarly, in PL the rate of tertiary attainment of younger cohorts increased by about 20 percentage points (OECD 2014), supporting the idea that most of the skill gain is due to an increase in participation to (and completion of) education.

c) Finally, the other important difference with age effect is that, on top of positive and negative, a “no effect” has also been detected: it involves individuals with tertiary education in countries like CZ, FI, IT, BE, NL, who do not show lower performances compared to older cohorts (with the same educational attainment). This is a positive outcome but still, subject to some *caveats*: as said before, preserving the same level of skill through generations may be a positive outcome if the initial level of skills is relatively high; on the contrary, if the original level of skill is low and it does not improve across generations, the final outcome may be a sub-optimal situation.

Table 14. Summary of empirical analysis: Cohort effect

COHORT EFFECT																	
positive						no effect						negative					
higher education			low-medium education			higher education			low-medium education			higher education			low-medium education		
top	medium	bottom	top	medium	bottom	top	medium	bottom	top	medium	bottom	top	medium	bottom	top	medium	bottom
				IT	IT		CZ						DK		DK		
				IE	IE		FI					SE			SE		
					PL		IT						UK		CZ		
					FI		BE					IE					
					UK		NL										

Chapter 4. Drivers of skills: changes in the sectoral composition of the economy. A demand-side perspective[44]

4.1. Introduction and preliminary analysis

As already discussed in the previous chapter, there are two main drivers of skill change that have been identified in the literature: (i) technical and (ii) economic factors (see De Grip and Van Loo, 2002; Desjardin and Warnke, 2012). This section takes a demand-side perspective on the issue of skill drivers, by concentrating on the second category of factors: the changing economic context, and in particular, the changing sectoral composition of the economy. Assuming a limited labour mobility within a country (and within an administrative region), the distribution of economic activities (or sectors) is normally taken as given or pre-determined by any potential worker looking for a job. Accordingly, the distribution of economic sectors will be an accurate reflection of the available job opportunities the worker might be able take, based on his skills, experience and education profile. This will leave the worker vulnerable to sudden fluctuations in labour demand. While the distribution of economic sectors is generally quite stable within a country (or an administrative region) over the short-term, there might be important changes observable over a longer time frame. Some situations can create important policy challenges, for example in case there is a large local employer or a high dependency on a particular economic sector (a good example is the public administration sector in some low-income regions). Also, some other economic sectors might be highly exposed to international factors (e.g. globalization and off-shoring); large and sudden fluctuations in these factors might hinder the adjustment in local labour supply or hamper policy actors to tackle the consequences generated by changes in labour demand.

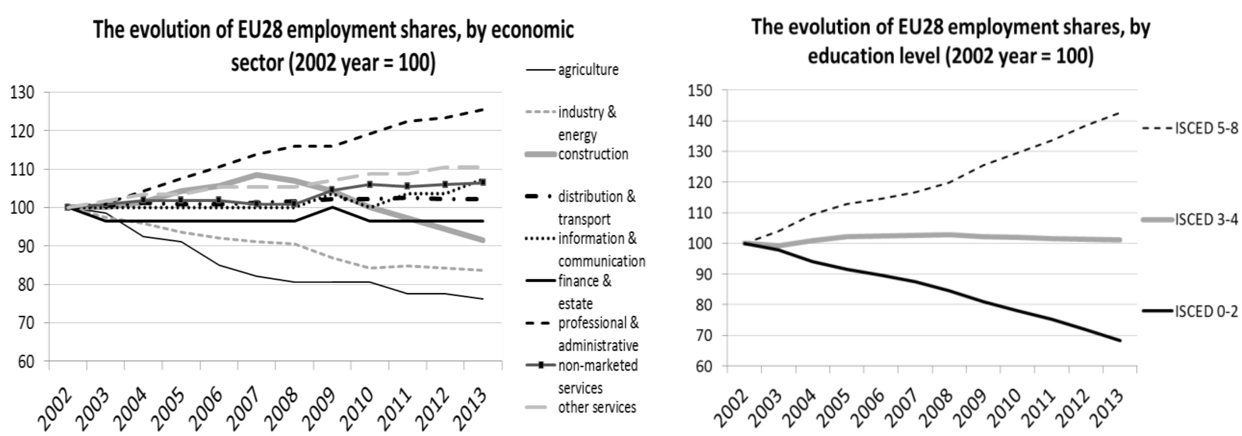
This chapter relies on theoretical insights and standard empirical methods to investigates how changes in the economic sectoral composition, a proxy for changes in the labour demand, might affect labour supply. The analysis tries to look at the consequences generated by changes in the economic context in terms of industry-specific skills and education attainment levels. The overall aim is to understand how sudden variations in the labour demand can be addressed, how their potentially negative consequences can be mitigated, by which policy actors, and which economic sectors are the most exposed ones.

[44] This chapter was prepared by Catalin Dragomirescu-Gaina The author would like to acknowledge useful comments received from Stan van Alphen, Elena Meroni, Luca Pappalardo and Esperanza Vera-Toscano on previous versions of this chapter.

Our analytical process starts with a first look of the available statistical data, including a careful analysis of past trends. The next figure provides an illustration of the main changes in the composition of employment. The left panel in Figure 13 shows the evolution of employment shares disaggregated by main economic sector, at the EU28 level between 2002 and 2013. The right panel in Figure 13 illustrates the evolution of employment shares, disaggregated by educational attainment, at the EU28 level and over the same time period.

In particular, the left panel of the figure shows an important increase in the employment share of sectors such as information & communication, professionals & administrative activities. At the same time, the employment shares have decreased considerably in other more traditional sectors like, for example, industry/manufacturing, construction and agriculture sectors. Alternatively, the right panel shows a significant increase in the employment share of tertiary educated individuals (i.e. ISCED 5-8) and a similar decrease in the employment share of people without an upper secondary education degree (i.e. ISCED 0-2).

Figure 13. The evolution of employment shares, by economic sector, and by education level



Note: Figures are compared to the initial period (2002), when all employment shares have been rescaled to equal 100.
Source: Eurostat, tables [nama_nace10_e] and [lfsa_egaed] respectively.

Intuitively, there seems to be a direct relationship between the developments observed in the two panels of the Figure 13 above. This is not by accident; an extensive empirical literature is documenting similar changes in employment distribution over the last decades in the context of skill-biased technological progress: a growing labour demand in service-related (more labour intensive) sectors has been associated with an increase in education attainment (see Acemoglu 2002, 2011; Autor and Dorn 2009). Yet, a more detailed analysis will need to take into account the full range of interactions between the two sides of the labour market, i.e. demand and supply. In this preliminary analysis, we will use (changes in) the sectorial composition as a proxy for (changes in) labour demand; alternatively, we will use (changes in) the education type as a proxy for (changes in) labour supply.

We draw some preliminary insights from analysing employment characteristics associated with the 'industry type' and the 'education type', accounting for both time and cross-sectional dimensions. A simple pairwise correlation[45] analysis can provide some interesting entry points for our latter discussion. We use data on employment shares for all EU-28[46] MS provided by Eurostat for the time period 1995-2013. We split the employment series along two different dimensions:

- educational attainment; we differentiate between three groups using the standard international (ISCED) classification: ISCED 0-2, ISCED 3-4, ISCED 5-8;
- economic sector; we differentiate between the following sectors, based on industrial classification used by the Eurostat (NACE): agriculture (NACE A), industry & energy (NACE B-E), manufacturing (NACE C), construction (NACE F), information & communication (NACE J), distribution & transport (NACE G-I), professional & administrative (NACE M-N), non-marketed services (NACE O-Q) and other activities (NACE R-U).[47] Table 15 below provides a summary description of the labels used throughout this chapter, associated with different groupings of NACE sectors; a complete description of NACE codes can be found at the end in Table A35 (see also Table A36 for summary statistics).

Table 15. Specific groupings of different economic sectors, based on NACE classification[48]

NACE code	Labels used throughout this chapter	Description
A	'agriculture'	Includes NACE A
B-E	'industry & energy'	Includes NACE codes B, C, D and E.
C	'manufacturing'	Includes NACE code C.
F	'construction'	Includes NACE sector F
J	'information & communication'	Includes NACE sector J
G-I	'distribution & transport'	Includes NACE codes G, H and I.
K-L	'finance & estate'	Includes NACE codes K and L
M-N	'professional & administrative'	Includes NACE codes M and N.
J+M-N	'new sectors'	Includes NACE J, M and N
O-Q	'non-marketed services' or 'public sector'	Includes NACE codes O, P and Q.

[45] Pairwise correlation coefficients are estimated using pairs of country-specific and year-specific values of each indicator included in the analysis.

[46] A separate similar analysis which looks at old and new MS (those joining after 2004) is provided in Table A37. Despite the fact that countries are pooled together in two groups, the differences between old and new MS are striking. Extending this analysis to country level, one might derive from here some important differences in the dynamics of sectoral employment shares in response to various local and global factors. See for example OECD (2007) for a very detailed policy report on the impact of globalization and offshoring on sectoral employment.

[47] Since we are dealing with employment shares in an economy characterized by N economic sectors, we only need to identify N-1 sectors to obtain a complete description of the economy. We have excluded the sector labeled as 'finance' in the table below including: financial and insurance services(NACE K) together with real estate activities (NACE L). At the EU28 level NACE K sector represents less than 3% of the total employment, while NACE L sector represents around 1% in total employment.

[48] NACE is a standard abbreviation for 'Nomenclature generale des Activites economiques dans les Communautes europeennes'.

R-U	'other services'	Includes NACE codes: R, S, T, U.

Table 16: Pairwise correlations derived using changes in employment

	INDUSTRY				SERVICES				
Education / Sector	**A**	**B-E**	**C**	**F**	**J**	**G-I**	**M-N**	**O-Q**	**R-U**
ISCED 0-2	**0.03**	**0.10****	**0.12****	**0.20*****	**-0.02**	**0.02**	**-0.12****	**-0.26*****	**-0.21*****
ISCED 3-4	**0**	**-0.05**	**-0.02**	**0.01**	**-0.06**	**0.03**	**0.04**	**-0.03**	**0.05**
ISCED 5-8	**0.03**	**-0.07**	**-0.11****	**-0.29*****	**0.10***	**-0.07**	**0.02**	**0.38*****	**0.08**

Note: Pairwise correlations were derived using changes in employment shares over a 3-years interval, for all EU28 countries. As a robustness check, we replicate the analysis using 5-years changes in employment shares, but results were similar. The ***, ** and * denote statistical significance at 1%, 5% and 10% level, respectively.

The insights provided by this simple correlation analysis are consistent with the overall story illustrated in Figure 13. Indeed, the correlations depicted in Table 16 illustrate a positive association between changes in the employment share of low educated individuals and changes in the employment shares of industry (including manufacturing) and construction sectors. There is a negative association between the employment share of low-educated individuals and the employment shares of professional & administrative, other services and public sectors. Correspondingly, changes in the employment share of highly educated individuals are negatively associated with the changes in employment shares in manufacturing and construction sectors. We also find empirical evidence of a positive correlation between the dynamics of employment for highly educated individuals and the dynamics of employment in the information & communication and public sectors. These correlations provide a snapshot of the past observed interactions between our selected proxies of labour demand and supply. Moreover, these interesting findings are in line with the insights provided by the 'skill-biased technological progress' theoretical framework, for which there is a strong empirical support in the literature (see Acemoglu 2002, 2011; Autor and Dorn 2009).

We draw more insights by splitting the EU28 countries into old and new MS (see also Table A37 in Appendix A) and highlight the differences between the two groups. While there are many similarities with the previous findings (drawn from analysing the entire EU28 sample), one main difference is worth mentioning here. There is a stronger positive association in the new MS than in the old MS between high skilled labour and employment in the new sectors, i.e. information & communication and professionals & administrative support sector. This hints at a more dynamic labour market in the new MS compared to old MS, especially for high skilled individuals. It also goes in the same direction with the idea that a higher labour market payoff (which might be proxied by higher labour productivity) has a higher contribution to expected (higher) education attainment in new MS than in old MS (see Dragomirescu-Gaina and Weber, 2013).

Yet, a simple correlation analysis might demonstrate its limits, especially if we try to add a more causal interpretation to these findings. The most important shortcoming is that such a pairwise correlation analysis will fail to fully account for the inherent endogeneity between labour supply and demand. There is an extensive literature pointing at the endogeneity problem arising between the education decisions and the economic context (see Acemoglu and Pischke, 2001; Kahn, 2010; Altonji et al., 2014; Restuccia and Vandenbroucke, 2014). However, addressing this topic goes beyond the scope of the present analysis. The next sections of this chapter will look at whether changes in the economic context might have consequences in terms of industry-specific skills and education attainment levels. We will only concentrate on modelling the dynamics of labour demand, by main economic sector and over the long-term, taking labour supply as exogenous in this process. The overall aim is to understand how policy actors could mitigate the negative consequences generated by exogenous changes in labour demand and what are the policy levers that can be employed, and at which level, in order to smooth the required adjustment in labour supply.

As mentioned in the introduction of this chapter, labour demand might change significantly over the long-term, changes that will be reflected in the distribution of economic sectors within the economy. These changes in labour demand might well go beyond the (short-term) possibilities of adjustment in labour supply and thus create shortages or excesses in the market place. Some exogenous factors driving changes in labour demand have already been mentioned before: globalization and off-shoring, international competition, and even discretionary policy actions etc. Since exogenous factors are an important source of uncertainty for many policy actors, their impact needs to be analysed in a more consistent way. It is to these exogenous demand shifters that we turn our attention to in the next sections of this chapter. Our aim is thus to highlight their importance and to suggests ways to counter their unfavourable influence on the decision-making process.

4.2. Econometric analysis

This section aims to provide some empirical insights into what have been the main drivers of change in the employment distribution, by economic sector over the last two decades in the EU as a whole. In an increasingly globalized economic environment, labour demand shifts have become a major source of concern. Employment distribution can be very sensitive to exogenous shocks such as shifts in: consumers' preferences, international (energy) prices, property and residential prices, discretionary government actions etc. These factors can have important implications for policy actions that aim to smooth the required adjustment in labour supply, like for example in the case of education and training policies.

Since education is a long-term undertaking, some policy actions needed to address labour market imbalances might have a limited impact, while others might be more effective. Students graduating from the vocational education system might be particularly vulnerable to sudden shifts in the employment distribution[49]. These students usually have a narrow set of specific skills that allows them

[49] There are limited options with respect to adjustments in labour supply required by offset such changes in labour demand. The options with a faster observable impact, such as reallocation and re-training, generally imply costs that must be paid either by the authorities or by the individual himself. Off-shoring and globalization have particularly affected low-skilled individuals. Adjusting the education system to the new economic context looks like a viable alternative, but it generally requires a longer planning and implementation horizon.

to perform a very specific set of tasks in a given economic sector (usually manufacturing or industry in general). Instead, students graduating with higher levels of general skills and competences (e.g. from upper secondary and tertiary education system) might be less vulnerable to such changes in labour demand. This is more so because labour mobility generally increases with education level (see Rodriguez, 2013), making these individuals more likely to search for employment opportunities elsewhere, across different regions, industries or even occupations.[50]

In this section, we want to empirically identify some of the main exogenous factors that drive changes in labour demand for EU28 as a whole.[51] As a first step, we try to select the best variables to use as proxies for labour demand shifts over the medium-to-long term. We rely on both empirical and theoretical literature to provide us with sufficient indications for our identification purposes. As a second step, we estimate several empirical model specifications, in a panel setting, using annual changes in employment shares for the major economic sectors described in the previous section.

A short review of the relevant literature suggests several important determinants for sectoral employment dynamics. For the tradable sector, which includes industry (and more specifically manufacturing), the single most important determinant is the degree of international price competitiveness.[52] This sector produces internationally tradable goods in a highly competitive global market, where relative costs and prices are essential to gain access and increase market share (see Campa and Goldberg, 1997; Gourinchas 1999; Goldberg and Tracy, 2000; Klein et al., 2003).

The output of the non-tradable sector, instead, can only be consumed domestically. This is the case for residential properties, public goods and services, and most of the private services. While there might be some global influences affecting the non-tradable sector (e.g. off-shoring in the information & communication sector), this sector is mostly shielded from international competition and therefore is more sensitive to domestic developments. For example, construction sector output is driven by local housing prices, but also bank lending activity, credit standards and monetary shocks to a large extent (see Zhu, 2005; Iacoviello and Neri, 2010). Most private and public services tend to be relatively more labour intensive than manufactured goods and this explains the higher sensitivity of (un)employment to changes in domestic aggregate demand (see Anderton et al., 2014). The higher labour intensity is also an argument used by the corporate sector for out-sourcing some activities which are not directly related to the main output. Out-sourcing might improve the overall labour productivity in the economy and also

[50] We disregard the risks associated with skill mismatch and prefer to focus the discussion on factors affecting labour mobility.

[51] A similar but more complex approach (e.g. involving dynamic simultaneous equations to insure coherence) stays at the basis of every methodology dealing with occupational and skills forecast (see CEDEFOP, 2012). Instead, we take a more simple approach here since our goal is to provide only some practical insights into the mechanics of this type of methodology. Our empirical analysis is obviously set in a partial equilibrium framework. Although we do control for changes in labour supply along some major dimensions (i.e. age brackets and education attainment levels), our modelling setting does not have the full consistency embedded in a general equilibrium model. Structural changes in labour market institutions is an important determinant of changes in sectorial composition, industrial relations and labour market dynamics in general (see Bassanini and Ernst, 2002). However, we are not able to control for this determinant, due to limited data availability with respect to indicators measuring changes in labour market institutions (the one computed by OECD is only available every 5 years).

[52] Other determinants might refer to industry concentration, monopolistic power, sector-specific import penetration rate etc.

create additional labour demand for those services included in the intermediate consumption of the corporate sector.

In the case of public services and publically provided goods, the output of the sector is largely determined by government budget constraints. Therefore, the employment dynamics must be sensitive to the amount of public financial resources available. Even in this context, exogenous fluctuations in employment might be determined by discretionary fiscal policy actions, which generally follow short-term political motivations rather than long-term motivations. Obviously, some public sector employees with sector-specific skills, such as those working in the health-care or the education sector, will bear the brunt of these discretionary policy adjustments (e.g. severe austerity measures and significant cuts in public wages have been implemented in Romania and Greece right after the economic crisis).

4.2.1. Empirical specifications

In this section, we attempt to model employment dynamics in the following major economic sectors: industry (NACE B-E), construction (NACE F), information & communication (NACE J), professional & administrative (NACE M-N) sectors, distribution & transport (NACE G-I) and public sector (NACE O-Q). We use standard regression analysis on a panel dataset covering all EU28 countries and spanning over the 1995-2013 period. We draw on the insights provided by the literature and concentrate only on few exogenous labour demand shifters for which there is good data availability. More specifically, we model employment dynamics for:

- industry sector – by relying on exogenous changes in relative prices (i.e. real exchange rate deflated by unit labour cost indexes) as a potential explanatory variable;
- construction sector – by relying on lagged changes in residential property prices[53] as an explanatory factor;
- information & communication sector together with professional & administrative sector – by relying on lagged changes in gross domestic spending on R&D per inhabitant[54];
- distribution & transport sector – by relying on lagged changes in labour productivity as a proxy for out-sourcing incentives in the corporate sector;
- public sector – by relying on lagged changes in real government spending as a potential explanatory factor.

The equation below gives a more formal illustration of the model specification for the dynamics of employment share in a synthetic economic sector labelled NACE X:

$$\begin{aligned}\Delta\,(employment\_share\_NACEX)_{c,t} \\ = \alpha + \beta * \Delta\,(employment\_share\_DEMO)_{c,t-1} + \gamma * \Delta(MACRO)_{c,t-k} + \delta_t + \vartheta_c + \epsilon_{c,t}\end{aligned}$$

[53] Source: Bank for International Settlements - residential property price statistics, available at www.bis.org/statistics/pp.htm.

[54] We group these sectors together since both seem to respond to the same economic determinants.

where c and t are country and time indexes, Δ is the annual change in the indicator and k is an appropriate time lag. The $employment\_share\_DEMO$ is a proxy for demographic or labour supply characteristics and $MACRO$ is a macroeconomic variable proxying the economic context. The δ_t, ϑ_c are year-specific and country-specific terms, while α, β, δ are model coefficients. ϵ is the model's residual.

We added controls for lagged changes in labour supply, that can affect current employment dynamics, and include the following variables: (i) changes in the employment shares for individuals with high and medium education attainment (ISCED 5-8 and ISCED 3-4 respectively); and (ii) changes in the employment shares for young individuals and adults (age brackets 15-24 and 25-49). We use the first or, at most, the second lags[55] of these regressors to make sure that they are exogenous in relation to the explained employment dynamics.

We present two sets of estimates for our empirical models. The first set of estimates, displayed in Table A38, refers to one way least-squares dummy variable (LSDV) estimates for the basic model specification that includes as additional controls year-specific dummies[56]. The second set of estimates, displayed in Table A39, further corrects for any remaining autocorrelation in the model's residuals, by adding country-specific terms.[57] Since all models are estimated in first-differences, the included country-specific terms are in fact proxies for country-specific linear trends in employment shares.

The estimated models explain reasonably well the dynamics of employment in the above mentioned sectors, especially in the case of industry and public sectors. The model specification for the construction sector delivers the highest explanatory power (i.e. as measured by its R^2), but it does not pass the residual autocorrelation test (even after the inclusion of country-specific linear trends) so that the interpretation of the results must be dealt with care. The model specifications explaining the dynamics of employment in the 'new sectors' seems to point at the importance of R&D spending as an important determinant; however, this determinant loses its statistical significance when we include country-specific linear trends in equation, meaning that other time invariant factors (such as institutional characteristics related to the R&D area[58]) might be important. Notice the low explanatory power model specification associated with the distribution & transport sector; even including country-specific terms does not significantly increase the explanatory power of the model (R^2 would rise from 0.06 to only 0.18).

[55] The only exception is for the case of real exchange rate (which is clearly exogenous with respect to domestic employment dynamics), where we did not use lagged values of the independent variable, but contemporaneous ones.

[56] The first set of estimates includes only year dummies to control for other omitted global factors which might affect all EU28 countries in the same time.

[57] The second set of estimates additionally includes country-specific terms as a proxy for country-specific trends in employment shares. With the notable exception of construction sector employment, the second set of estimates passes the required residual autocorrelation test (see Arellano and Bond, 1991).

[58] Examples of such institutional factors relate to: organization of the research institutions and universities, funding arrangements, international career prospects, researchers' mobility, incentives for research excellence etc.

4.2.2. Results and policy discussion

In this section, we would like to focus the discussion on the macroeconomic factors identified above, used to explain changes in sectoral employment shares over the last two decades across the EU.

The industry sector is mostly producing internationally tradable goods, being exposed to global competition from companies located in other countries.[59] Consequently, its employment share is particularly sensitive to changes in the relative labour costs, i.e. domestic versus foreign costs. For a representative industry firm, an increase in such costs would reduce labour demand and thus sectoral employment (when compared to total employment) either because higher prices will reduce competitiveness and the firm might lose its export market share or because outsourcing can relocate the production in other countries where costs are lower. These findings are in line with the conclusions emerging from other studies investigating similar aspects (see Goldberg and Tracy, 2000; Hijzen et al., 2005; OECD, 2007). What is worth mentioning is the statistical relevance of country-specific factors in the best model specification; this highlights the importance of domestic/local unobserved characteristics, whose particular importance is validated empirically by our approach above.

The employment share in the construction sector seems particularly responsive to residential price changes. Yet, this simple model specification is not well adapted to capture other aspects which might be important such as long-term interest rates[60], lending and private credit dynamics. Some recent empirical studies analysing the European housing and mortgage markets show that banks' credit standards drive most of the market dynamics (see Ott, 2014). However, there is nothing to explain these credit standards (except, maybe, the discretionary behaviour of the commercial banks), thus leaving the initial problem unsolved with respect the identification of the structural drivers in this sector.

Changes in the employment share of the distribution & transport sector seem to be sensitive to past changes in productivity dynamics. Since most of these services are part of the intermediate consumption of the corporations (and not final consumption of the households), any past productivity improvements would likely reflect an increase in corporate demand for these services (e.g. due to the need for externalization and out-sourcing). Interestingly, adding country specific terms to correct for potential autocorrelation in the residuals, does not seem to be required in this case. However, the overall explanatory power of the specification remains very low, highlighting the idea that the increase in employment for the distribution & transport sector has been a common development across EU countries, with a low observed variation across EU countries (see also Table A36).

We also find that changes in the employment share of the new (technology) sectors, including here information & communication together with professional & administrative services, are driven by changes in R&D spending per capita. However, this does not seem to be such an empirically robust

[59] It should be noted however, that some of the sectors included in this broad category produce goods which are cannot be directly traded on the international market (such as distribution of electricity in NACE D sector or waste management in NACE E sector).

[60] The specification including the lagged values for the long-term interest rates, deflated by consumption deflator, does not improve the overall explanatory power of the empirical model, nor does it solve the specification tests outlined above.

finding, since including country-specific factors will remove the importance of spending as a determinant of employment in these sectors. This suggests that institutional factors might play a bigger role than the changes in spending capacity and financial resources mobilized for R&D. An example can be found in the positive interactions between Silicon Valley, a world hub for start-ups and technology companies, and Stanford University, one of the world top universities (see Saxenian, 1996).

Meanwhile, changes in the employment share of the public sector seem to be driven by past changes in government spending, which was to be expected. Here again, as in the case of industry employment shares, we see that the explanatory power and the statistical properties of the model improve when adding country-specific factors; these factors might reflect local characteristics with respect to traditional fiscal policy considerations, specific needs in the provision of public goods (e.g. high health-care costs due to unfavourable demographics) or other local influences that are both country-specific and time invariant within the context of our analysis.

Our short empirical analysis has exposed some of the main determinants of sectoral employment that appear to be robust over time and across (EU) countries. Understanding their consequences could help mitigate the inherent uncertainty that arises with respect to the implementation of education policies in a changing economic context. This is a challenge in itself, because most of the exogenous factors identified above are either outside the control of policy-makers or might be subject to some binding external constraints.[61]

Our estimates also highlight the importance of country-specific factors that might drive specific trends in sectoral employment shares, especially for the industry sector, but also for the 'new sectors' and the public sector. These findings have substantial policy implications. The industrial sector is more likely to employ individuals with low-education attainment (please refer back to Table 16) but with very specific skills, a situation which might raise unemployment challenges. In particular, the design of vocational education systems might require specific policy actions especially in those countries (or regions) where the labour demand might be concentrated or overly reliant on specific industries. In contrast, the 'new sectors' generally employ high-skilled individuals, but funding seems to be less important than institutional characteristics (e.g. organization of the research institutions, international career prospects and mobility of researchers, incentives for research excellence etc.). We believe this analysis could also be extended to lower administrative units, such as regions. However, caution is advisable in this case, because the higher labour mobility would make local characteristics less relevant. We conclude that a more detailed analysis of the trade-offs between labour mobility and local characteristics might be needed in order to have a better understanding of the required policy actions.

[61] In contrast to all the other exogenous determinants identified in the previous section, government spending is fully under the control of the government (public authorities). However, when it comes to education policies, the general government budget might be subject to hard constraints that can limit potential policy actions with respect to education, training or other policies that aim at smoothing the transition from education to the labour market.

4.3. A fast-forward look at labour market needs

Anticipating labour market needs could make a valuable contribution to policy analysis for both, policy makers involved in designing and implementing education policies, and those dealing with economic and labour market policies. The drawback is that, in the context of an increasingly globalized world, future labour market needs might be very difficult to anticipate. Moreover, an important part of the labour market dynamics might be driven by several *exogenous factors* on which policy makers have, at most, a limited control. As specifically discussed in the previous sections, these factors interact with some (local) institutional characteristics that govern the functioning of different economic sectors, for example, in terms of job creation and destruction, incentives for labour mobility or education and re-training opportunities. It illustrates the complex interactions that take place along the demand and supply dimensions of the labour market. In this context, a better outcome can be achieved by improving the coordination between labour market policies on the one side and education and training policies on the other side.

The need for coordination brings an additional constraint on education and training policies with respect to timing. Relevant questions might refer to: how and when to change the design the education system, the institutional framework and the curriculum in order to avoid shortages and to produce graduates that best fit the (future) labour market needs. One can easily assume that every year about one individual will be entering the labour force for approximately every forty individuals already working. But this very simple assumption implies a huge time lag between an implemented change in education policies and any relevant economic consequences. It also means that, when trying to accommodate labour market needs, authorities need to be proactive and to anticipate labour market developments, as accurately as possible.

Such a proactive stance might have favourable consequences on the outcomes of the vocational education system where many tracks are determined as a function of specific labour market needs, in a close cooperation between authorities and employers or employees' unions. In countries where vocational education is more developed, local employers are traditionally involved in different ways by, for example, suggesting curriculum or offering apprenticeship placement. Some countries have also developed specific structures and institutions that can offer a wide range of tools such as career guidance, job placement and specific training for young individuals.

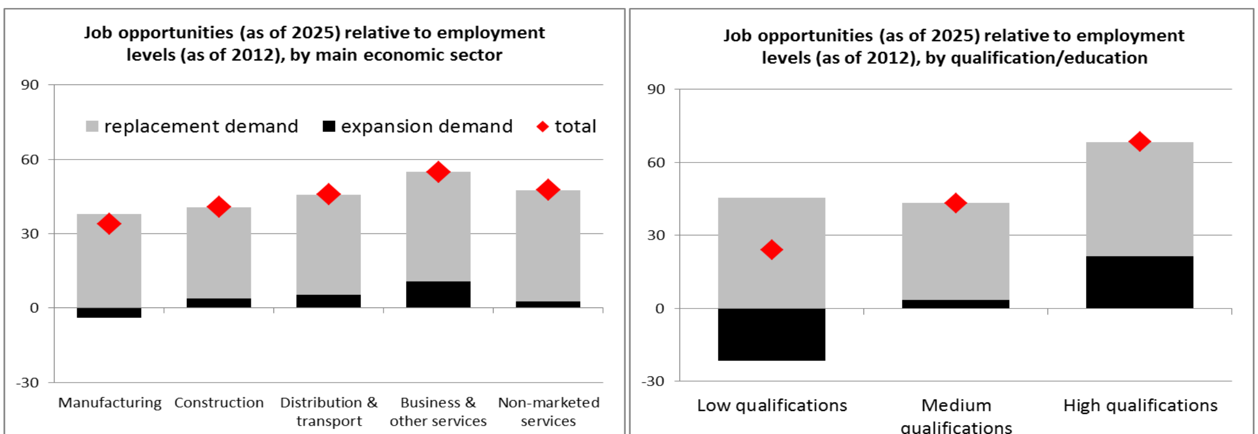
At the level of the European Union[62], some institutions provide significant contributions to the study of interactions between labour market prospects and education policies. The European Centre for the Development of Vocational Training (CEDEFOP) produces long-term skill forecasts (for methodological aspects, see CEDEFOP, 2012) for each EU Member State (MS). The forecasts are based on a comprehensive macroeconomic modelling approach, where equilibrium employment is determined by supply and demand interactions. The forecasts provide rough, but important indications, for both EU and national policy makers, with respect to what are the priorities that need to be emphasised in terms

[62] Occupational forecasts for the U.S. labour market are being made available by the Bureau of Labor Statistics (see U.S. Department of Labor, 2014).

of education and sector-specific skills. Policy actions can be designed to improve job-matching by preventing labour market shortages/excesses from occurring, provide training in accordance with labour market needs, increasing mobility within and across various economic sectors etc.

The latest CEDEFOP forecasting exercise, which extends up to 2025, paints an interesting and in the same time challenging picture for the European labour markets. When disaggregating by main economic sector[63], one can see that the increase in job opportunities will be driven more by *replacement* demand and less by *expansion* demand. The *replacement* demand arises due to individuals retiring or leaving the labour force and can be more easily anticipated because it is mainly driven by demographics and/or migration flows. The *expansion* demand is determined within the framework of the labour market dynamics, at the interaction between endogenous labour supply changes and exogenous demand shifters. The next figure displays the number of total employment opportunities, by main economic sector, projected to be generated between 2013 and 2025 at the EU28 level, considering both components, replacement and expansion respectively (according to the latest CEDEFOP skill forecasts).

Figure 14: Total job opportunities relative to employment levels at the EU28 level.



Source: CEDEFOP (2013) skill forecast[64]

Note: The y-axis represents the percentage of total job opportunities as of 2025 relative to employment levels as of 2012. The two components of total job opportunities from the two panels above (i.e. expansion and replacement, respectively) do not sum up in relative terms (as depicted in the figure), but only in absolute terms (i.e. headcounts).

According to this CEDEFOP forecast, the employment trends observed in the last two decades (please refer back to Figure 13) will likely continue over the next decade (see Figure 14). If we maintain the assumption that the same correlations uncovered in the previous sections hold between economic sectors and education levels (qualifications), we can make the following observations. Firstly, the need for replacement in the manufacturing sector will require a constant number of fresh graduates from the

[63] CEDEFOP is using very similar groupings of economic sectors as the ones used in this chapter. Please refer back to Table 15. The only difference between us and CEDEFOP concerns the additional sector labeled as 'business & other services', which includes NACE codes K, J, L, M, N, R-U.

[64] Available at http://www.cedefop.europa.eu/en/events-and-projects/projects/forecasting-skill-demand-and-supply/skills-forecasts-detailed-data

education system, and most likely from the vocational education system. The total employment (in headcounts) will be nevertheless smaller compared to current employment levels in the manufacturing sector (i.e. 2012 in the CEDEFOP forecasting exercise). Secondly, higher increases with respect to current employment levels are projected in the distribution & transport, the business & other services and the public (non-marketed services) sectors. This will likely maintain pressure on all levels of the education system to deliver graduates, specifically with upper secondary and tertiary education credentials.

The previous section has concentrated on explaining changes in employment shares over time, when disaggregating by main economic sector. But the same changes in employment can be directly related to *expansions* in demand profiles[65] (in CEDEFOP terminology). The previous sections have uncovered the key role played by the country-specific factors for both industry and public sectors employment dynamics. These two sectors broadly correspond to manufacturing and non-marketed services in the CEDEFOP terminology. The next figure displays the projected changes over the 2013-2025 horizon in employment shares, by country, and by main economic sector. As the figure below confirms there is a higher cross-country variation in the upper panel (manufacturing and public sectors) compared to the bottom panel. In fact, the cross-section standard deviations of the projected change in employment shares are: 5.91% for manufacturing; 6.91% for public sector; 4.86% for distribution & transport; 4.67% for business & other services.

Figure 15: Relative change in employment shares, by sector, and by country, 2025-2013 period

Source: CEDEFOP (2012) skill forecasts.

Note: Changes in employment shares are computed using expansion demand by each economic sector relative to total expansion demand.

[65] The job opportunities generated by replacement demand were only indirectly considered in the empirical exercise from the previous section (i.e. when adding the lagged changes in labour supply proxies as additional regressors).

The CEDEFOP projection thus confirms the importance of country-specific factors or institutional characteristics in driving the sectoral employment shares. This seems to be the case especially for the industrial/manufacturing sector and the public sector. It is highly possible that, at a more disaggregated level, the contribution of local characteristics[66] to employment dynamics could be dominated by the effects generated by labour mobility. However, this seems unlikely in the case of manufacturing and public sectors. Firstly, the manufacturing sector generally employs a higher share of low-to-medium skilled individuals, which are less mobile across occupations, industries and regions. Secondly, the public sector is generally more rigid (less flexible), highly unionized and dominated by risk-averse employees with a lower degree of mobility.

4.4. Conclusions

Over the long-term, labour supply is largely determined by demographics and education policies, two slow paced determinants that can be easily predicted. However, labour demand can remain a key source of policy uncertainty. Rapid and long-lasting changes in labour demand have been brought about by several exogenous factors, on which policy makers have a limited control. These factors interact with some (local) institutional characteristics that govern the functioning of different economic sectors (for example, in terms of hiring/firing regulations, job creation and destruction, incentives for labour mobility or education and re-training opportunities).

We suggest that a better understanding of the consequences, in terms of sectoral employment dynamics, could help different policy actors make the right changes along some key institutional dimensions. This might help smooth the required adjustment in labour supply, especially when it comes to addressing potential labour market shortages/excesses in the industry (manufacturing) or the new (technology) sectors. Careful considerations should be made especially in cases where a lack of proper incentives might impede on high-skilled labour mobility in new technology sectors. For low- and medium-skilled or risk-averse workers, such as those working in manufacturing or public sectors, less flexible institutions or strict labour market regulations (with respect to hiring and firing) might hamper the required adjustment in supply.

Another conclusion could be that, given the inherent uncertainties surrounding the policy making process, a better outcome might be achieved under a better coordination of education and labour market policies. The empirical analysis and the insights derived from analysing available projections at the EU level confirm the importance of including all those country/local-specific characteristics that are fundamental in determining the employment outcome of a country, a region or a community.

[66] For example traditions in manufacturing, natural resources availability etc.

Conclusions

While it is widely known that higher levels of education matter in determining better employment opportunities and, in general, in higher level of welfare due to higher wages and positive social outcomes (social integration and active citizenship), the role and the extent of the actual level of cognitive skills possessed by the individual has received little scholarly attention.

Human capital is an encompassing concept including educational level, work experience and several types of skills including cognitive and soft-skills; among many other factors related to the supply side of labour, such as socio-demographic characteristics, it has been identified as the major predictor of occupational chances. Nonetheless, the multifaceted nature of human capital and the limited type of data available to properly measure it have up to now limited the range of investigation in this field, mainly recurring to partial measures of human capital such as educational level and work experience. The release of the international survey on adult skills PIAAC opened up a new set of possibilities for research in the field of cognitive skills, making it possible to separate the contribution of at least two of the main components of human capital, i.e. educational attainment and actual skills. Although it is not possible to identify a proper casual impact, a positive association between education, skills and employment opportunities has been observed, suggesting that part of the positive effect of education may pass through the level of skills possessed by the individual.

Thus, the main aim of this report is to fill the gap of knowledge about: (1) the level and distribution of cognitive skills in the working-age population (Chapter 1); (2) the role played by these skills in determining employment opportunities (Chapter 2); and (3) the evolution of skills both across individuals and along their lifespan (Chapter 3). In effect, skills are correlated to educational qualifications, but the two do not automatically match: as shown in previous research undertaken by CRELL-JRC (Flisi et al. 2014), the level of actual skill can vary widely among individuals with the same educational level. Besides, unlike formal education attainment which is fixed after the end of the formal process of learning, skills are a dynamic concept evolving over time as confirmed by a wide literature on the phenomenon of skill loss or, less often, skill gain as discussed in Chapter 3. Finally, to complement our analysis, and further emphasise the need to invest in skill acquisition, Chapter 4 partially investigates how changes in the economic sectorial composition, a proxy for changes in the labour demand, might affect labour supply. The analysis looks at the consequences generated by changes in the economic context in terms of industry-specific skills and education attainment levels (educational attainment is used as a proxy for individual abilities).

The most relevant findings emerging from the report are summarized here:

- **Countries differ in average values of skills but also in their distribution:** some countries may have higher averages than others, but lower values at top quantiles, meaning a lower proportion of high achievers and vice versa. As an example, CZ and SK have better average values than other countries, but have lower proportions of high achievers compared to DE or UK, which on average, perform worse than CZ and SK. The contrary can be said for FI, which on average is the top performing country, whose bottom 5% however, performs worse than the bottom 5% of CZ, SK, CY.

Most of the debate among academics, but also the general public, occurring at each release of the PISA or PIAAC surveys is about differences in country performances, expressed in average values. However, the comparison of average values leaves most of the story behind the scene: more informative and policy relevant is the process of looking at the whole distribution of skills among the population, with particular attention to the two tails of the distribution, representing the share of high and low achievers.

- **The level of skills is positively associated not only to employment opportunities, but also to the type of occupation in which individuals are employed**: higher skill levels are positively and significantly associated to higher employment probability in most of the 17 European countries studied (DE, DK, EE, ES, FI, IE, SE, UK), even after controlling for several socio-economic factors. The relationship is less clear in the rest of the countries: positive but not significant for AT, CY, CZ, IT, PL; with mixed results for BE, FR, NL, SK. However, for all the countries studied (with the only exception of CY) higher skill levels are positively and significantly associated to the probability of being employed in a skilled professional or semi-skilled white collar occupation.

- **The impact of skills varies across countries:** there is a general trend of increasing employment opportunities with increasing education and skills, however, cross country differences have been observed. In few countries, namely FI, SE and UK, the level of skill has a greater or equal impact than the educational attainment, meaning that individuals with high skills have greater or the same occupational chances of individuals with higher educational attainment but lower skills; on the contrary, in BE, CY, CZ, FR and PL only educational qualifications have a significant impact on employability, irrespective of the actual level of skills possessed by the individual.

These findings are relevant for policy makers as they suggest that investing in the enhancement of individual skills may lead to different outcomes according to the country of implementation: in countries where the labour market (namely employers) is able to acknowledge and reward differences in the endowment of skills of employees, these policies may lead to successful outcomes. On the other hand, lower effects may be observed in countries where educational qualifications are the main (or only) determinant of labour market integration, and where the allocation to high skilled professions passes through educational credentials only, decoupled from the actual level of skills of the employee. In this case, policies oriented to underline and attribute value to skills may proceed along with policies for the strengthening of workers’ skills.

Since empirical evidence showed that skills also evolve over time, the report further investigates the skills dynamic from this point of view. The literature has highlighted a general tendency of deterioration of skills associated to increasing age; however, what at first sight may appear as a consequence of the ageing process, has been disentangled as the result of two different phenomena, i.e. the ageing and the cohort effect. Several other factors have been isolated as intervening variables affecting the distribution of skills during the lifetime of an individual (as an example lifelong learning, the type of occupation, social activity and in general health conditions). However, due to the wide scholarly recognition that age and cohort effect enjoy in the literature, recognizing them as the main drivers of changes in the distribution of skills, and due to limited availability of data, Chapter 3 has been devoted to observe to what extent the deterioration of skills is driven by ageing rather than cohort effect. This distinction is significant in terms of policy implications: knowing the source of skill deterioration is the fundamental first step for designing specific measures able to effectively contrast the problem. In fact, whether the process of deterioration of skills in a society occurs through the lifetime of an individual or rather across different generations does make a difference and raises the flag for targeted interventions at policy level. In brief:

- **A general negative effect of age is observable in all the European countries analysed:** as age increases the level of skills decreases. The age effect hits differently individuals according to their level of education, original level of skills (bottom, medium, top quantile), may happen earlier or later in time, nevertheless it comes out as a common feature for all countries.

This result suggests the need of policies specifically oriented to prevent skill loss after the end of formal education, or at different points in time, according to the shape of the process of ageing. In this respect, lifelong learning policies are often considered the best suitable option for contrasting the deterioration of skills with age. However, general lifelong learning does not seem to contribute much in slowing down the process of deterioration: the phenomenon of skill loss affects all countries, even those where adult participation in lifelong learning is widespread (as DK, FI, NL) and, as shown in the analysis, participation in lifelong learning is not associated to a slower pace of the process of deterioration of skills.

Besides, an important feature in terms of policy implications is who is most affected by the age effect: in fact, in DK, FI, NL, CZ, BE, SE, PL, IT, IE, UK, when individuals with medium-low levels of education (and thus already disadvantaged in terms of employment opportunities, as investigated in Chapter 2) get older, further worsen their set of skills, therefore increasing their original disadvantage. The most worrisome scenario is the one represented by individuals with low education and low skills in DK, NL, and FI: here these individuals already have the lowest level of skills, compared to the rest of the population in their country, and moreover, they are also those deteriorating even further the already low initial level.

Thus, intervention targeted at slowing down the pace of the deterioration of skills with age would be beneficial to all European countries; however, it seems that a general intervention might not be enough. As shown in the analysis, particular attention has to be paid to specific target groups; in particular low educated people with low levels of skills are the most at risk of deteriorating their already weak position in the labour market.

- **The cohort effect has a different impact across countries and educational level:** some countries succeeded in improving the skill level of younger cohorts of low-medium educated individuals (IT, IE, PL, FI, UK) and kept stable the performances of individuals with tertiary education (CZ, FI, IT, BE, NL) compared to their older counterparts. On the contrary, in some other countries a deterioration in the endowment of skills of younger generations has been observed (compared to older birth cohorts), among both high and low educated people (DK, SE), among highly educated individuals only (UK, IE) or among low-medium educated individuals only (CZ).

These findings raise the flag for some structural changes which may have negatively influenced the process of skill acquisition by younger cohorts. In fact, although the analysis performed cannot clearly define which factors determined the deterioration of skills in younger cohorts, it points to the fact that a worsening in the overall performance of the educational system across birth cohorts took place. At the same time, a positive effect per se is not enough for detecting a "success" of a national education system, since the initial distribution of skills (as seen in Chapter 1) also needs to be taken into consideration. Indeed, the improvement registered in a country can still mean an overall lower level of skill, if compared to another country with higher starting level, which may not have improved because there was no longer room for improvement. This example fits well the case of PL and IT, which started with general low level of skills among older birth cohorts and caught up (in particular PL) thanks to higher participation to education, and of FI, which already had high levels of completion of upper secondary and tertiary education with also best performances in terms of skills.

In terms of policy implications, the loss of skills between generations is a big concern: it may result in a loss of competitiveness and well-being in broader terms for the whole society, but it is also particularly relevant if we consider that younger cohorts have to face a more competitive labour market, requiring higher level of skills in information and communication technology due to the higher proportion of automatized processes and the increasing technological complexity which involves all occupational sectors, even low skilled occupations. Thus, the cohort effect has to be carefully taken into consideration, first in light of the positive social outcomes associated to education and higher skills, potentially leading to some inequalities in the set of opportunities that different generations can enjoy, but also, and more directly linked to the whole aim of this research, in light of the increasing complexity of the labour market for a successful integration of individuals in the economic sector.

- **Indeed, consistent with the considerations about the increasing complexity of the labour market, the observed trends from Chapter 4 go in the direction of a concentration of employment in sectors requiring higher educational level and, quite likely, high skilled workers.** Over the last decades, rapid and long-lasting changes in labour demand have been brought about by several exogenous factors, on which policy makers have a limited control. This source of uncertainty can be mitigated by a careful analysis and understanding of the main drivers of labour demand, with an emphasis on local specific characteristics. The empirical findings presented in this Chapter also highlight the importance of including an anticipatory component in the analysis of labour market trends, especially with respect to the interaction between vocational education systems and industrial/manufacturing employment. Anticipating market needs and placing a higher emphasis on country-specific and/or regional characteristics could avoid labour shortages. Careful considerations should be made in particular in cases where less flexible market institutions and strict regulations might impede on labour mobility, especially with respect to low-to-medium skilled and risk-averse workers.

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Appendix. Tables

Table A1. IALS sample size per country (respondents aged 16-65)

IALS 1st cycle (1994-96)	N	IALS 2nd cycle (1998)	N
Belgium (Flanders)	2,261	Chile	3,502
Canada	4,500	Czech Republic	3,132
Germany	2,062	Denmark	3,026
Ireland	2,423	Finland	2,928
Netherlands	2,837	Hungary	2,593
New Zealand	4,223	Italy	2,974
Poland	3,000	Norway	3,307
Sweden	2,645	Slovenia	2,972
Switzerland	2,826	Switzerland (Italian)	1,302
United Kingdom	6,718		
United States	3,038		
Total	*36,533*	*Total*	*25,736*

Table A2. PIAAC sample size per country (respondents aged 16-65)

Country	Frequency	Country	Frequency
Australia	8,600	Japan	5,278
Austria (AT)	5,130	Korea	6,667
Belgium (BE Fl)	5,463	The Netherlands (NL)	5,170
Canada	27,285	Norway	5,128
Cyprus (CY)	5,053	Poland (PL)	9,366
Czech Republic (CZ)	6,102	Russian Federation	3,892
Denmark (DK)	7,328	Slovak Republic (SK)	5,723
Estonia (EE)	7,632	Spain (ES)	6,055
Finland (FI)	5,464	Sweden (SE)	4,469
France (FR)	6,993	England/Northern Ireland (UK)	8,892
Germany (DE)	5,465	United States	5,010
Ireland (IE)	5,983	*Total – 17 EU countries*	*104,909*
Italy (IT)	4,621	*Total*	*166,679*

Table A3. Activity rate in European countries (annual averages for 2013)

	Males	Females
European Union (28 countries)	77.9	66.0
Belgium	72.7	62.3
Bulgaria	72.2	64.5
Czech Republic	80.5	65.1
Denmark	80.6	75.6
Germany	82.6	72.6
Estonia	78.6	71.8
Ireland	77.0	62.7
Greece	76.9	58.3
Spain	79.8	68.7
France	75.4	66.9
Croatia	68.9	58.5
Italy	73.4	53.6
Cyprus	80.6	67.2
Latvia	76.6	71.6
Lithuania	74.7	70.3
Luxembourg	76.3	63.2
Hungary	71.7	58.8
Malta	79.4	50.2
Netherlands	84.7	74.6
Austria	81.2	71.1
Poland	73.9	60.1
Portugal	76.5	69.8
Romania	72.7	56.5
Slovenia	74.2	66.6
Slovakia	77.2	62.5
Finland	76.8	73.4
Sweden	83.3	78.8
United Kingdom	82.1	70.9

Source: Eurostat. Online code: *lfsi_act_a*

Table A4. Number of individuals participating in the PIAAC survey and selected working sample by country

Country	Original sample	Working sample
Austria (AT)	5,130	5,022
Belgium (BE Fl)	5,463	4,977
Cyprus (CY)	5,053	4,386
Czech Republic (CZ)	6,102	6,073
Denmark (DK)	7,328	7,282
Estonia (EE)	7,632	7,564
Finland (FI)	5,464	5,454
France (FR)	6,993	6,906
Germany (DE)	5,465	5,373
Ireland (IE)	5,983	5,963
Italy (IT)	4,621	4,583
The Netherlands (NL)	5,170	5,082
Poland (PL)	9,366	9,342
Slovak Republic (SK)	5,723	5,682
Spain (ES)	6,055	5,960
Sweden (SE)	4,469	4,466
England/Northern Ireland (UK)	8,892	8,780
Total (EU 17)	104,909	102,895

Note: Own elaboration from PIAAC data.

Table A5. Education and skills effects on employability – AT, BE and CY

	AT		BE		CY	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
Literacy skill level 2		-0.0427		0.348**		0.205
		(0.122)		(0.122)		(0.136)
Literacy skill level 3		0.190		0.239		0.104
		(0.129)		(0.125)		(0.138)
Literacy skill level 4 and 5		-0.0265		0.384*		0.374
		(0.177)		(0.171)		(0.214)
Medium education	0.748***	0.724***	0.831***	0.792***	0.749***	0.735***
	(0.094)	(0.096)	(0.096)	(0.097)	(0.102)	(0.105)
High education	1.237***	1.191***	1.560***	1.497***	1.663***	1.635***
	(0.139)	(0.145)	(0.117)	(0.126)	(0.122)	(0.128)
Age group 16-24	-1.117***	-1.132***	-2.477***	-2.499***	-1.972***	-1.963***
	(0.163)	(0.162)	(0.166)	(0.167)	(0.193)	(0.194)
Age group25-34	-0.353*	-0.360*	-0.239	-0.251	0.0143	0.0175
	(0.153)	(0.152)	(0.162)	(0.162)	(0.142)	(0.142)
Age group 45-54	-0.158	-0.146	-0.333*	-0.336*	-0.282*	-0.277*
	(0.139)	(0.140)	(0.140)	(0.141)	(0.130)	(0.130)
Age group 55-64	-2.364***	-2.335***	-2.543***	-2.534***	-1.357***	-1.355***
	(0.128)	(0.131)	(0.133)	(0.134)	(0.133)	(0.133)
Female	-0.323***	-0.318***	-0.631***	-0.627***	-0.980***	-0.986***
	(0.077)	(0.077)	(0.078)	(0.078)	(0.091)	(0.091)
Married	0.573***	0.571***	0.721***	0.718***	0.241	0.240
	(0.100)	(0.100)	(0.103)	(0.104)	(0.127)	(0.127)
Presence of children in the household	-0.145	-0.144	0.142	0.144	0.0634	0.0665
	(0.122)	(0.122)	(0.120)	(0.121)	(0.144)	(0.144)
High parental education (socio-economic background)	-0.602***	-0.582***	-0.388*	-0.315*	-0.163	-0.139
	(0.117)	(0.118)	(0.152)	(0.154)	(0.159)	(0.159)
Foreign-born	0.0717	0.0514	0.216*	0.189*	-0.136	-0.148
	(0.095)	(0.096)	(0.095)	(0.095)	(0.113)	(0.112)
Constant	1.251***	1.184***	1.063***	1.210***	0.889***	0.964***
	(0.178)	(0.185)	(0.177)	(0.186)	(0.187)	(0.193)
N	5022	5022	4977	4977	4386	4386

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A6. Education and skills effects on employability – CZ, DE and DK

	CZ.		DE		DK	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
Literacy skill level 2		0.249		0.351**		0.497***
		(0.208)		(0.117)		(0.095)
Literacy skill level 3		0.137		0.518***		0.691***
		(0.208)		(0.122)		(0.101)
Literacy skill level 4 and 5		0.262		0.356*		0.722***
		(0.257)		(0.162)		(0.155)
Medium education	1.327***	1.324***	1.002***	0.925***	0.518***	0.405***
	(0.175)	(0.176)	(0.102)	(0.103)	(0.081)	(0.082)
High education	1.814***	1.798***	1.586***	1.431***	1.276***	1.050***
	(0.215)	(0.219)	(0.128)	(0.136)	(0.094)	(0.102)
Age group 16-24	-2.782***	-2.783***	-0.546***	-0.608***	-0.679***	-0.783***
	(0.231)	(0.232)	(0.154)	(0.154)	(0.151)	(0.152)
Age group25-34	-0.810***	-0.804***	-0.120	-0.119	-0.434**	-0.460***
	(0.191)	(0.191)	(0.140)	(0.140)	(0.137)	(0.137)
Age group 45-54	0.0672	0.0791	0.243	0.277*	0.0359	0.0658
	(0.244)	(0.239)	(0.139)	(0.139)	(0.128)	(0.128)
Age group 55-64	-2.149***	-2.139***	-1.202***	-1.155***	-1.462***	-1.390***
	(0.183)	(0.182)	(0.125)	(0.127)	(0.105)	(0.107)
Female	-0.626***	-0.624***	-0.570***	-0.570***	-0.428***	-0.446***
	(0.114)	(0.114)	(0.077)	(0.077)	(0.066)	(0.067)
Married	0.0127	0.0176	0.789***	0.776***	0.574***	0.554***
	(0.128)	(0.127)	(0.096)	(0.096)	(0.082)	(0.082)
Presence of children in the household	-0.614***	-0.613***	-0.0771	-0.0546	0.184	0.190
	(0.167)	(0.166)	(0.117)	(0.117)	(0.108)	(0.107)
High parental education (socio-economic background)	-0.0468	-0.0535	0.00871	-0.0591	0.0566	0.00390
	(0.175)	(0.175)	(0.122)	(0.125)	(0.075)	(0.076)
Foreign-born	-0.245	-0.237	-0.444***	-0.353**	-0.766***	-0.578***
	(0.239)	(0.241)	(0.123)	(0.126)	(0.082)	(0.088)
Constant	1.459***	1.537***	0.514**	0.636**	0.869***	1.009***
	(0.292)	(0.302)	(0.186)	(0.197)	(0.158)	(0.165)
N	6073	6073	5373	5373	7282	7282

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A7. Education and skills effects on employability – EE, ES and FI

	EE		ES		FI	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
Literacy skill level 2		0.152		0.250**		0.459***
		(0.092)		(0.081)		(0.128)
Literacy skill level 3		0.270**		0.364***		0.922***
		(0.094)		(0.097)		(0.130)
Literacy skill level 4 and 5		0.409**		0.400*		0.873***
		0.152		0.250**		0.459***
Medium education	1.056***	1.009***	0.618***	0.543***	0.967***	0.850***
	(0.073)	(0.074)	(0.082)	(0.084)	(0.086)	(0.088)
High education	1.857***	1.770***	1.257***	1.135***	1.648***	1.412***
	(0.092)	(0.095)	(0.084)	(0.091)	(0.125)	(0.133)
Age group 16-24	-1.201***	-1.247***	-1.447***	-1.481***	-1.408***	-1.497***
	(0.119)	(0.120)	(0.130)	(0.130)	(0.154)	(0.156)
Age group25-34	-0.0730	-0.0852	0.00854	0.00328	-0.494***	-0.529***
	(0.114)	(0.114)	(0.105)	(0.105)	(0.141)	(0.142)
Age group 45-54	-0.256*	-0.241*	-0.0437	-0.0271	-0.121	-0.0753
	(0.107)	(0.107)	(0.093)	(0.093)	(0.142)	(0.143)
Age group 55-64	-1.330***	-1.321***	-1.119***	-1.066***	-1.420***	-1.298***
	(0.099)	(0.099)	(0.098)	(0.100)	(0.128)	(0.131)
Female	-0.355***	-0.357***	-0.510***	-0.498***	-0.0923	-0.105
	(0.061)	(0.061)	(0.064)	(0.065)	(0.071)	(0.071)
Married	0.490***	0.479***	0.316***	0.299**	0.584***	0.556***
	(0.069)	(0.069)	(0.091)	(0.091)	(0.082)	(0.082)
Presence of children in the household	0.287**	0.303**	0.0128	0.0297	0.257*	0.281**
	(0.092)	(0.092)	(0.098)	(0.098)	(0.100)	(0.100)
High parental education (socio-economic background)	0.182*	0.160*	0.00793	-0.0268	0.0457	-0.0395
	(0.073)	(0.073)	(0.081)	(0.082)	(0.087)	(0.090)
Foreign-born	-0.519***	-0.477***	-0.218*	-0.155	-0.608**	-0.343
	(0.091)	(0.092)	(0.101)	(0.102)	(0.190)	(0.185)
Constant	0.187	0.196	0.355**	0.423***	0.367*	0.287
	(0.128)	(0.134)	(0.111)	(0.116)	(0.160)	(0.171)
N	7564	7564	5960	5960	5454	5454

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A8. Education and skills effects on employability – FR, IE and IT

	FR		IE		IT	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
Literacy skill level 2		0.253**		0.295**		0.00443
		(0.088)		(0.099)		(0.106)
Literacy skill level 3		0.167		0.365***		0.295*
		(0.094)		(0.104)		(0.122)
Literacy skill level 4 and 5		0.0551		0.556***		0.288
		(0.135)		(0.156)		(0.221)
Medium education	0.501***	0.430***	0.763***	0.686***	0.651***	0.599***
	(0.114)	(0.119)	(0.084)	(0.086)	(0.090)	(0.092)
High education	1.171***	1.107***	1.571***	1.438***	1.393***	1.305***
	(0.126)	(0.136)	(0.098)	(0.105)	(0.146)	(0.150)
Age group 16-24	-1.972***	-1.981***	-1.117***	-1.141***	-2.482***	-2.506***
	(0.123)	(0.123)	(0.127)	(0.127)	(0.177)	(0.179)
Age group25-34	-0.252*	-0.255*	0.0394	0.0404	-0.575***	-0.573***
	(0.108)	(0.108)	(0.099)	(0.099)	(0.127)	(0.127)
Age group 45-54	0.136	0.137	0.185	0.193	-0.146	-0.141
	(0.103)	(0.104)	(0.105)	(0.106)	(0.121)	(0.121)
Age group 55-64	-1.465***	-1.471***	-0.478***	-0.461***	-1.655***	-1.638***
	(0.094)	(0.095)	(0.106)	(0.107)	(0.124)	(0.125)
Female	-0.502***	-0.504***	-0.437***	-0.425***	-1.311***	-1.315***
	(0.060)	(0.060)	(0.070)	(0.070)	(0.088)	(0.088)
Married	0.539***	0.536***	0.588***	0.567***	0.0824	0.0732
	(0.074)	(0.074)	(0.080)	(0.080)	(0.110)	(0.110)
Presence of children in the household	0.0117	0.00620	-0.460***	-0.462***	-0.219	-0.196
	(0.093)	(0.093)	(0.089)	(0.089)	(0.113)	(0.113)
High parental education (socio-economic background)	0.101	0.0921	0.189*	0.146	-0.0936	-0.136
	(0.069)	(0.070)	(0.077)	(0.079)	(0.109)	(0.110)
Foreign-born	-0.474***	-0.448***	-0.407***	-0.364***	0.275	0.328*
	(0.097)	(0.098)	(0.088)	(0.088)	(0.161)	(0.162)
Constant	0.625***	0.795***	0.116	0.207	1.480***	1.422***
	(0.156)	(0.168)	(0.117)	(0.126)	(0.132)	(0.142)
N	6906	6906	5963	5963	4583	4583

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A9. Education and skills effects on employability – NL, PO and SE

	NL		PL		SE	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
Literacy skill level 2		0.131		0.102		0.610***
		(0.129)		(0.097)		(0.149)
Literacy skill level 3		0.440***		0.139		0.989***
		(0.132)		(0.101)		(0.155)
Literacy skill level 4 and 5		0.314		0.163		1.308***
		(0.164)		(0.147)		(0.189)
Medium education	0.576***	0.503***	0.964***	0.946***	1.170***	1.011***
	(0.088)	(0.090)	(0.097)	(0.097)	(0.106)	(0.109)
High education	1.154***	1.030***	2.253***	2.207***	1.654***	1.284***
	(0.109)	(0.116)	(0.120)	(0.124)	(0.134)	(0.142)
Age group 16-24	-0.794***	-0.812***	-1.481***	-1.506***	-1.735***	-1.783***
	(0.170)	(0.170)	(0.127)	(0.128)	(0.194)	(0.196)
Age group25-34	-0.176	-0.160	-0.386**	-0.389**	-0.673***	-0.675***
	(0.165)	(0.165)	(0.126)	(0.126)	(0.171)	(0.172)
Age group 45-54	-0.123	-0.0937	-0.376**	-0.373**	0.166	0.204
	(0.140)	(0.140)	(0.127)	(0.127)	(0.181)	(0.182)
Age group 55-64	-1.671***	-1.612***	-1.738***	-1.738***	-1.129***	-1.016***
	(0.127)	(0.130)	(0.124)	(0.124)	(0.150)	(0.154)
Female	-0.644***	-0.634***	-0.989***	-0.996***	-0.458***	-0.453***
	(0.077)	(0.077)	(0.069)	(0.070)	(0.088)	(0.089)
Married	0.555***	0.543***	0.380***	0.372***	0.666***	0.660***
	(0.101)	(0.101)	(0.095)	(0.095)	(0.103)	(0.104)
Presence of children in the household	-0.0733	-0.0614	0.118	0.123	0.0106	0.0517
	(0.123)	(0.122)	(0.103)	(0.103)	(0.137)	(0.138)
High parental education (socio-economic background)	-0.0222	-0.0663	0.110	0.0958	0.164	0.0547
	(0.085)	(0.085)	(0.090)	(0.091)	(0.109)	(0.112)
Foreign-born	-0.960***	-0.863***	-0.340	-0.337	-0.676***	-0.300*
	(0.120)	(0.124)	(0.618)	(0.611)	(0.115)	(0.125)
Constant	1.519***	1.426***	0.359*	0.403*	0.736***	0.706***
	(0.176)	(0.184)	(0.156)	(0.165)	(0.202)	(0.214)
N	5082	5082	9342	9342	4466	4466

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A10. Education and skills effects on employability – SK and UK

	SK		UK	
Specification	(1)	(2)	(1)	(2)
Literacy skill level 2		0.309*		0.444***
		(0.123)		(0.110)
Literacy skill level 3		0.439***		0.715***
		(0.123)		(0.117)
Literacy skill level 4 and 5		0.199		0.742***
		(0.174)		(0.158)
Medium education	1.491***	1.414***	0.677***	0.543***
	(0.094)	(0.096)	(0.093)	(0.096)
High education	2.221***	2.142***	1.065***	0.867***
	(0.132)	(0.135)	(0.101)	(0.108)
Age group 16-24	-2.069***	-2.086***	-1.411***	-1.390***
	(0.154)	(0.154)	(0.133)	(0.135)
Age group25-34	-0.506***	-0.502***	-0.224	-0.220
	(0.123)	(0.123)	(0.116)	(0.115)
Age group 45-54	0.266*	0.260*	0.0659	0.0809
	(0.124)	(0.124)	(0.116)	(0.117)
Age group 55-64	-1.314***	-1.329***	-1.250***	-1.250***
	(0.114)	(0.115)	(0.110)	(0.111)
Female	-0.687***	-0.700***	-0.585***	-0.591***
	(0.072)	(0.072)	(0.075)	(0.076)
Married	0.479***	0.479***	0.543***	0.509***
	(0.100)	(0.100)	(0.080)	(0.081)
Presence of children in the household	-0.313*	-0.315*	-0.301**	-0.284**
	(0.127)	(0.128)	(0.094)	(0.095)
High parental education (socio-economic background)	0.475***	0.428***	0.221**	0.104
	(0.086)	(0.088)	(0.082)	(0.084)
Foreign-born	-0.194	-0.208	-0.451***	-0.321**
	(0.228)	(0.227)	(0.111)	(0.113)
Constant	-0.170	-0.0727	1.002***	1.122***
	(0.163)	(0.170)	(0.137)	(0.145)
N	5682	5682	8780	8780

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: age group 35-44, low education level, literacy skill level 1 or below. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A11. Education and skills effects on type of occupation – AT, BE, CY, CZ, DE, DK

	AT	BE	CY	CZ	DE	DK
Skilled occupations						
Literacy skill level 2	0.954***	1.260***	0.159	0.946**	1.057***	0.792***
	(0.239)	(0.231)	(0.338)	(0.355)	(0.247)	(0.187)
Literacy skill level 3	2.203***	2.054***	0.284	1.681***	1.702***	1.228***
	(0.280)	(0.250)	(0.354)	(0.377)	(0.256)	(0.197)
Literacy skill level 4 and 5	2.088***	2.353***	0.745	3.352***	2.097***	1.867***
	(0.426)	(0.407)	(0.530)	(0.599)	(0.368)	(0.337)
Medium education	2.204***	0.986***	2.252***	2.920***	2.369***	1.449***
	(0.205)	(0.221)	(0.292)	(0.539)	(0.256)	(0.163)
High education	4.340***	3.885***	4.477***	5.774***	4.615***	3.685***
	(0.430)	(0.322)	(0.399)	(0.868)	(0.340)	(0.225)
Semi-skilled white-collar occupations						
Literacy skill level 2	0.308	0.734***	-0.0128	1.062**	0.397	0.829***
	(0.206)	(0.197)	(0.315)	(0.332)	(0.203)	(0.177)
Literacy skill level 3	1.102***	1.342***	-0.214	1.623***	0.638**	0.843***
	(0.258)	(0.221)	(0.334)	(0.362)	(0.222)	(0.190)
Literacy skill level 4 and 5	0.659	1.677***	-0.206	3.287***	0.509	1.248***
	(0.420)	(0.396)	(0.527)	(0.585)	(0.362)	(0.334)
Medium education	1.572***	0.360*	1.690***	1.462***	1.652***	1.000***
	(0.184)	(0.182)	(0.247)	(0.418)	(0.200)	(0.142)
High education	1.774***	1.324***	2.357***	2.632**	1.991***	1.315***
	(0.438)	(0.307)	(0.370)	(0.812)	(0.314)	(0.220)
Semi-skilled blue-collar occupations						
Literacy skill level 2	-0.0807	0.645**	-0.118	0.776*	0.272	0.253
	(0.210)	(0.209)	(0.345)	(0.324)	(0.212)	(0.184)
Literacy skill level 3	0.322	0.842***	-0.269	0.764*	0.156	-0.105
	(0.265)	(0.241)	(0.369)	(0.352)	(0.234)	(0.199)
Literacy skill level 4 and 5	-0.928*	0.939*	-1.345	1.343*	-0.342	-0.623
	(0.464)	(0.426)	(0.707)	(0.610)	(0.398)	(0.403)
Medium education	1.161***	0.237	0.650*	0.931*	1.503***	0.906***
	(0.187)	(0.192)	(0.274)	(0.421)	(0.217)	(0.151)
High education	2.145***	0.172	0.396	0.767	1.552***	0.650**
	(0.436)	(0.352)	(0.425)	(0.880)	(0.333)	(0.248)
N	3644	3299	2710	3610	3991	5271

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: low education level, literacy skill level 1 or below. The regression includes controls for age group, gender, marital status, family structure, parental education, and migrant background. Reference category for the multinomial model: unskilled occupation.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A12. Education and skills effects on type of occupation – EE, ES, FI, FR, IE, IT

	EE	ES	FI	FR	IE	IT
Skilled occupations						
Literacy skill level 2	0.401*	0.556**	0.394	1.068***	0.515*	0.729**
	(0.191)	(0.199)	(0.291)	(0.162)	(0.243)	(0.245)
Literacy skill level 3	0.820***	1.012***	1.178***	1.248***	1.028***	0.969***
	(0.194)	(0.222)	(0.293)	(0.182)	(0.267)	(0.276)
Literacy skill level 4 and 5	1.442***	2.461***	1.979***	2.270***	1.498***	2.952***
	(0.278)	(0.720)	(0.342)	(0.468)	(0.419)	(0.774)
Medium education	1.798***	1.447***	1.269***	0.399	0.960***	2.464***
	(0.198)	(0.189)	(0.254)	(0.254)	(0.237)	(0.229)
High education	3.930***	3.191***	4.531***	3.350***	2.993***	5.596***
	(0.229)	(0.226)	(0.465)	(0.320)	(0.302)	(0.481)
Semi-skilled white-collar occupations						
Literacy skill level 2	0.165	0.117	0.428	0.985***	0.204	0.526*
	(0.184)	(0.158)	(0.272)	(0.151)	(0.223)	(0.209)
Literacy skill level 3	0.275	0.312	0.856**	0.870***	0.435	0.698**
	(0.188)	(0.191)	(0.275)	(0.175)	(0.252)	(0.249)
Literacy skill level 4 and 5	0.325	1.579*	1.171***	1.499**	0.744	2.327**
	(0.286)	(0.730)	(0.331)	(0.469)	(0.418)	(0.786)
Medium education	1.262***	0.893***	0.527*	0.446	0.467*	1.066***
	(0.175)	(0.157)	(0.211)	(0.243)	(0.216)	(0.190)
High education	1.823***	1.272***	1.499***	1.859***	0.955**	2.449***
	(0.218)	(0.213)	(0.450)	(0.313)	(0.293)	(0.479)
Semi-skilled blue-collar occupations						
Literacy skill level 2	0.185	-0.101	-0.112	0.515***	0.131	0.354
	(0.172)	(0.175)	(0.264)	(0.153)	(0.226)	(0.202)
Literacy skill level 3	-0.0810	-0.0994	0.0725	0.296	0.346	0.251
	(0.179)	(0.215)	(0.272)	(0.185)	(0.262)	(0.266)
Literacy skill level 4 and 5	-0.267	0.284	0.167	0.912	0.171	1.876*
	(0.290)	(0.790)	(0.334)	(0.495)	(0.445)	(0.826)
Medium education	0.443**	0.0653	0.348	0.127	0.0470	0.107
	(0.151)	(0.179)	(0.218)	(0.226)	(0.220)	(0.199)
High education	0.604**	0.482	0.234	0.797*	0.111	0.496
	(0.205)	(0.247)	(0.486)	(0.316)	(0.303)	(0.631)
N	5302	3310	3843	4432	3625	2809

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: low education level, literacy skill level 1 or below. The regression includes controls for age group, gender, marital status, family structure, parental education, and migrant background. Reference category for the multinomial model: unskilled occupation.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A13. Education and skills effects on type of occupation – NL, PO, SE, SK, UK

	NL	PL	SE	SK	UK
Skilled occupations					
Literacy skill level 2	1.328***	0.655**	1.471***	0.454	0.495
	(0.247)	(0.240)	(0.352)	(0.286)	(0.253)
Literacy skill level 3	1.596***	1.229***	1.757***	1.000***	1.585***
	(0.243)	(0.260)	(0.368)	(0.292)	(0.264)
Literacy skill level 4 and 5	2.571***	1.495***	2.325***	1.735**	2.456***
	(0.340)	(0.407)	(0.495)	(0.558)	(0.477)
Medium education	1.745***	1.935***	1.273***	2.909***	1.066***
	(0.169)	(0.362)	(0.311)	(0.315)	(0.205)
High education	3.293***	5.803***	4.112***	6.647***	2.900***
	(0.300)	(0.485)	(0.454)	(0.679)	(0.266)
Semi-skilled white-collar occupations					
Literacy skill level 2	0.861***	0.224	0.897**	0.630*	0.0151
	(0.222)	(0.218)	(0.310)	(0.282)	(0.208)
Literacy skill level 3	1.148***	0.380	0.887**	0.765**	0.661**
	(0.219)	(0.243)	(0.334)	(0.291)	(0.234)
Literacy skill level 4 and 5	1.701***	0.245	1.003*	1.676**	1.016*
	(0.325)	(0.393)	(0.470)	(0.555)	(0.464)
Medium education	1.180***	1.168***	0.694*	1.628***	0.898***
	(0.160)	(0.236)	(0.281)	(0.238)	(0.181)
High education	0.811**	3.207***	1.128*	3.598***	1.446***
	(0.308)	(0.403)	(0.439)	(0.658)	(0.258)
Semi-skilled blue-collar occupations					
Literacy skill level 2	0.651**	0.161	0.898**	0.238	0.117
	(0.248)	(0.200)	(0.326)	(0.249)	(0.229)
Literacy skill level 3	0.340	-0.102	0.477	0.407	0.748**
	(0.253)	(0.231)	(0.349)	(0.261)	(0.255)
Literacy skill level 4 and 5	0.677	-0.658	0.541	1.068	0.781
	(0.378)	(0.419)	(0.501)	(0.546)	(0.507)
Medium education	0.974***	0.740***	0.637*	0.761***	0.672***
	(0.186)	(0.199)	(0.290)	(0.200)	(0.198)
High education	0.467	1.333***	1.359**	0.821	0.645*
	(0.358)	(0.401)	(0.463)	(0.692)	(0.288)
N	3889	5012	3300	3269	5783

Notes: Own elaborations on PIAAC (2012) data. The reference categories are: low education level, literacy skill level 1 or below. The regression includes controls for age group, gender, marital status, family structure, parental education, and migrant background. Reference category for the multinomial model: unskilled occupation.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A14. Age effect on literacy skills – BE, CZ and DK

	BE		CZ		DK	
Age: 23-29	-7.676**		-7.875*		-8.896***	
	(2.590)		(3.879)		(2.459)	
Age: 30-36	-10.03***		-5.943		-13.89***	
	(2.233)		(3.492)		(2.644)	
Age: 37-43	-12.85***		-15.32***		-14.83***	
	(2.462)		(3.603)		(2.726)	
Age: 44-50	-16.07***		-18.31***		-20.18***	
	(2.571)		(3.421)		(2.374)	
Age: 51-57	-23.71***		-19.63***		-25.99***	
	(2.783)		(3.918)		(2.758)	
Age: 58-65	-26.44***		-22.67***		-35.52***	
	(3.093)		(3.572)		(2.505)	
Age		-0.630*		-1.145**		-0.279
		(0.293)		(0.403)		(0.268)
Age squared		0.000492		0.00761		-0.00594
		(0.004)		(0.005)		(0.003)
Female	-5.394***	-5.435***	-2.236	-2.237	-1.297	-1.270
	(1.205)	(1.213)	(1.560)	(1.559)	(1.179)	(1.173)
Medium education	21.23***	21.46***	15.93***	16.85***	23.23***	22.74***
	(2.009)	(2.045)	(3.043)	(2.950)	(2.026)	(2.002)
High education	50.16***	50.26***	42.59***	43.80***	46.20***	45.28***
	(1.813)	(1.915)	(4.082)	(3.745)	(2.019)	(1.947)
Mother's education: low	11.88*	11.94*	8.759	9.197	-11.54	-10.93
	(4.673)	(4.708)	(5.628)	(5.650)	(9.814)	(9.832)
Mother's education: medium	19.62***	19.45***	10.33	10.65	-6.763	-6.423
	(5.090)	(5.099)	(5.860)	(5.871)	(10.012)	(10.002)
Mother's education: high	26.78***	26.64***	15.97*	16.21*	1.714	1.821
	(4.969)	(5.000)	(6.959)	(7.006)	(9.946)	(9.962)
Father's education: low	5.772	5.696	-0.835	-0.636	9.321	8.929
	(3.954)	(3.948)	(5.068)	(5.091)	(9.016)	(8.950)
Father's education: medium	11.58**	11.52**	9.913	9.885	11.74	11.32
	(4.163)	(4.147)	(5.061)	(5.062)	(8.959)	(8.896)
Father's education: high	15.07***	15.06***	18.15**	18.18**	20.26*	20.09*
	(4.271)	(4.244)	(5.818)	(5.873)	(9.085)	(9.038)
Immigrant mother	-18.38***	-18.37***	-3.066	-2.762	-23.34***	-23.54***
	(2.976)	(2.977)	(4.320)	(4.326)	(3.161)	(3.158)
Immigrant father	-11.41***	-11.48***	-4.239	-4.188	-17.61***	-17.90***
	(2.775)	(2.764)	(3.801)	(3.800)	(2.836)	(2.843)
Constant	243.8***	254.4***	250.8***	269.0***	264.3***	269.8***
	(5.150)	(7.242)	(7.145)	(9.717)	(11.579)	(12.222)
Observations	4983	4983	6081	6081	7286	7286

Notes: Own elaborations on PIAAC (2012) data. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A15. Age effect on literacy skills – FI, IE and IT

	FI		IE		IT	
Age: 23-29	-2.186		-4.935		-10.34**	
	(2.480)		(2.953)		(3.503)	
Age: 30-36	-5.028		-2.103		-12.90***	
	(2.656)		(2.555)		(3.174)	
Age: 37-43	-7.874*		-3.507		-9.925**	
	(3.120)		(2.797)		(3.357)	
Age: 44-50	-14.20***		-8.215**		-10.36***	
	(2.730)		(3.187)		(3.114)	
Age: 51-57	-25.68***		-5.940*		-14.50***	
	(2.907)		(2.700)		(3.588)	
Age: 58-65	-38.25***		-10.59***		-24.98***	
	(2.628)		(2.947)		(3.380)	
Age		0.986**		-0.228		-0.130
		(0.317)		(0.340)		(0.365)
Age squared		-0.0232***		0.0000458		-0.00383
		(0.004)		(0.004)		(0.004)
Female	1.308	1.439	-5.773***	-5.723***	0.500	0.573
	(1.475)	(1.479)	(1.260)	(1.260)	(1.586)	(1.582)
Medium education	21.02***	20.53***	27.33***	27.30***	24.96***	23.89***
	(2.307)	(2.314)	(2.012)	(2.026)	(1.813)	(1.821)
High education	49.90***	49.12***	49.05***	49.07***	38.65***	36.48***
	(2.638)	(2.604)	(1.978)	(2.030)	(2.508)	(2.448)
Mother's education: low	27.28**	27.78**	11.94*	11.73*	-7.748	-6.397
	(9.967)	(10.063)	(5.550)	(5.591)	(13.155)	(13.038)
Mother's education: medium	31.01**	31.07**	19.35***	18.98**	0.619	1.877
	(10.175)	(10.272)	(5.810)	(5.847)	(13.407)	(13.308)
Mother's education: high	40.43***	40.42***	25.69***	25.22***	7.379	8.396
	(10.407)	(10.533)	(5.845)	(5.862)	(13.222)	(13.082)
Father's education: low	1.313	1.772	5.479	5.681	5.112	3.916
	(7.706)	(7.778)	(4.971)	(5.003)	(8.353)	(8.328)
Father's education: medium	7.251	7.618	12.15*	12.25*	11.06	9.823
	(7.556)	(7.621)	(5.121)	(5.143)	(8.450)	(8.468)
Father's education: high	14.27	14.76	17.51**	17.62**	14.47	14.00
	(7.900)	(7.961)	(5.387)	(5.424)	(9.649)	(9.622)
Immigrant mother	-36.93***	-36.90***	-13.26***	-13.43***	-5.515	-5.759
	(6.233)	(6.302)	(2.701)	(2.704)	(4.581)	(4.623)
Immigrant father	-28.27***	-28.44***	-5.868*	-5.892*	-25.39***	-25.83***
	(5.543)	(5.581)	(2.591)	(2.589)	(4.517)	(4.579)
Constant	247.0***	235.8***	227.8***	232.0***	250.9***	251.8***
	(8.156)	(8.941)	(6.312)	(9.371)	(12.569)	(14.062)
Observations	5464	5464	5963	5963	4589	4589

Notes: Own elaborations on PIAAC (2012) data. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A16. Age effect on literacy skills – NL and PL

	NL		PL	
Age: 23-29	-7.272**		-19.42***	
	(2.377)		(2.009)	
Age: 30-36	-9.821***		-26.51***	
	(2.812)		(2.676)	
Age: 37-43	-8.749***		-22.44***	
	(2.436)		(2.812)	
Age: 44-50	-16.75***		-24.32***	
	(2.427)		(3.035)	
Age: 51-57	-28.50***		-26.79***	
	(2.628)		(2.733)	
Age: 58-65	-35.33***		-31.63***	
	(2.438)		(2.738)	
Age		0.374		-2.035***
		(0.312)		(0.389)
Age squared		-0.0144***		0.0186***
		(0.004)		(0.005)
Female	-4.322***	-4.434***	3.662**	3.774**
	(1.267)	(1.259)	(1.368)	(1.368)
Medium education	26.41***	26.03***	16.07***	15.06***
	(1.796)	(1.811)	(2.189)	(2.226)
High education	48.93***	48.19***	48.68***	45.50***
	(1.819)	(1.839)	(2.735)	(2.794)
Mother's education: low	19.65*	19.78**	2.702	2.303
	(7.675)	(7.598)	(8.904)	(8.862)
Mother's education: medium	24.82**	24.84**	6.939	6.367
	(7.811)	(7.731)	(9.170)	(9.107)
Mother's education: high	33.86***	33.87***	21.03*	20.78*
	(7.908)	(7.870)	(9.843)	(9.780)
Father's education: low	9.873	9.795	5.936	5.924
	(6.319)	(6.349)	(6.679)	(6.638)
Father's education: medium	16.36*	16.35*	16.66*	16.49*
	(6.575)	(6.599)	(6.680)	(6.658)
Father's education: high	17.71**	17.81**	18.43**	18.66**
	(6.454)	(6.489)	(7.016)	(6.963)
Immigrant mother	-19.49***	-19.82***	2.219	2.361
	(2.807)	(2.789)	(4.027)	(4.075)
Immigrant father	-15.16***	-15.08***	4.355	4.919
	(3.194)	(3.192)	(4.319)	(4.266)
Constant	247.9***	244.3***	244.9***	272.9***
	(8.081)	(9.351)	(7.938)	(9.871)
Observations	5083	5083	9366	9366

Notes: Own elaborations on PIAAC (2012) data. All figures are weighted.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A17. Age effect on literacy skills – SE and UK

	SE		UK	
Age: 23-29	-5.555		8.068*	
	(3.005)		(3.530)	
Age: 30-36	-6.903*		13.42***	
	(2.942)		(3.151)	
Age: 37-43	-3.770		16.28***	
	(2.880)		(3.065)	
Age: 44-50	-7.317**		12.60***	
	(2.836)		(3.745)	
Age: 51-57	-15.53***		8.756**	
	(2.760)		(3.065)	
Age: 58-65	-24.16***		12.73***	
	(2.831)		(3.657)	
Age		0.816**		1.677***
		(0.316)		(0.372)
Age squared		-0.0161***		-0.0183***
		(0.004)		(0.004)
Female	-4.490**	-4.556**	-2.960	-2.968
	(1.556)	(1.561)	(1.552)	(1.550)
Medium education	23.21***	22.03***	27.29***	27.09***
	(2.023)	(2.013)	(1.944)	(1.940)
High education	50.94***	49.28***	43.21***	43.29***
	(2.163)	(2.090)	(2.039)	(2.055)
Mother's education: low	6.580	6.844	5.499*	5.750*
	(6.698)	(6.653)	(2.569)	(2.572)
Mother's education: medium	17.32*	17.30*	18.42***	18.91***
	(7.117)	(7.053)	(2.547)	(2.558)
Mother's education: high	21.32**	21.20**	27.77***	28.37***
	(7.331)	(7.235)	(3.674)	(3.701)
Father's education: low	2.499	2.281	1.122	1.025
	(4.836)	(4.819)	(2.399)	(2.401)
Father's education: medium	4.695	4.542	11.09***	11.09***
	(4.941)	(4.932)	(2.535)	(2.539)
Father's education: high	9.410*	9.477*	16.45***	16.34***
	(4.765)	(4.757)	(3.031)	(3.017)
Immigrant mother	-22.23***	-22.65***	-11.19***	-10.82**
	(2.616)	(2.606)	(3.331)	(3.304)
Immigrant father	-21.45***	-21.34***	-15.74***	-15.93***
	(2.469)	(2.439)	(3.194)	(3.209)
Constant	257.6***	246.4***	223.5***	199.4***
	(6.123)	(9.023)	(3.850)	(7.594)
Observations	4469	4469	8806	8806

Notes: Own elaborations on PIAAC (2012) data. All figures are weighted.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A18. Correspondence between cohorts in IALS and PIAAC.

AGE IN IALS	AGE IN PIAAC (+ 13)	AGE IN PIAAC (+ 15)	AGE IN PIAAC (+ 17)
16	16	16	16
17	17	17	17
18	18	18	18
19	19	19	19
20	20	20	20
21	21	21	21
22	22	22	22
23	23	23	23
24	24	24	24
25	25	25	25
26	26	26	26
27	27	27	27
28	28	28	28
29	29	29	29
30	30	30	30
31	31	31	31
32	32	32	32
33	33	33	33
34	34	34	34
35	35	35	35
36	36	36	36
37	37	37	37
38	38	38	38
39	39	39	39
40	40	40	40
41	41	41	41
42	42	42	42
43	43	43	43
44	44	44	44
45	45	45	45
46	46	46	46
47	47	47	47
48	48	48	48
49	49	49	49
50	50	50	50
51	51	51	51
52	52	52	52
53	53	53	53
54	54	54	54
55	55	55	55
56	56	56	56
57	57	57	57
58	58	58	58
59	59	59	59
60	60	60	60
61	61	61	61
62	62	62	62
63	63	63	63
64	64	64	64
65	65	65	65

COH1
COH2
COH3
COH4
COH5
COH6
COH7

Table A19. Age and cohort effect on literacy skills

	BE	CZ	DK	FI	IE	IT	NL	PL	SE	UK
Age: 23-29	-12.62***	-9.198***	-13.95***	-8.736***	-9.191***	-14.41***	-7.462***	-24.21***	-7.004**	2.016
	(2.687)	(2.178)	(1.965)	(2.302)	(2.296)	(2.700)	(2.125)	(2.099)	(2.521)	(2.618)
Age: 30-36	-26.02***	-24.44***	-30.00***	-19.79***	-11.76***	-18.18***	-11.85***	-27.89***	-17.35***	-7.023***
	(2.440)	(2.352)	(2.078)	(2.523)	(2.195)	(2.782)	(2.272)	(2.143)	(2.306)	(2.066)
Age: 37-43	-37.21***	-40.21***	-41.02***	-26.37***	-18.71***	-20.74***	-16.03***	-29.62***	-31.09***	-8.370**
	(3.179)	(2.687)	(2.662)	(2.992)	(2.707)	(3.256)	(2.211)	(2.428)	(2.735)	(2.870)
Age: 44-50	-46.53***	-55.11***	-58.18***	-33.57***	-30.78***	-17.32***	-23.48***	-36.34***	-37.36***	-21.53***
	(3.481)	(3.490)	(2.853)	(3.434)	(2.917)	(3.592)	(2.652)	(2.938)	(3.071)	(2.790)
Age: 51-57	-60.41***	-68.69***	-76.01***	-43.12***	-31.30***	-10.78**	-38.50***	-31.14***	-56.08***	-29.74***
	(3.626)	(3.735)	(3.287)	(3.850)	(3.262)	(3.781)	(2.892)	(3.270)	(3.270)	(3.190)
Age: 58-65	-69.07***	-81.33***	-89.49***	-54.89***	-39.71***	-21.07***	-47.25***	-39.07***	-72.02***	-39.55***
	(3.993)	(4.081)	(3.750)	(4.195)	(3.397)	(4.252)	(3.042)	(3.330)	(3.315)	(3.361)
Cohort 2	0.278	-8.191***	-10.12***	0.936	6.143*	17.95***	-4.073	24.60***	-21.25***	12.62***
	(2.738)	(2.207)	(1.751)	(1.930)	(2.875)	(2.260)	(2.236)	(2.954)	(2.789)	(2.188)
Cohort 3	-7.407**	-21.16***	-19.40***	3.535	1.825	22.27***	-5.305*	27.98***	-24.44***	-1.060
	(2.707)	(2.488)	(2.041)	(2.460)	(2.881)	(2.741)	(2.296)	(2.360)	(2.525)	(2.132)
Cohort 4	-12.35***	-31.69***	-27.61***	3.224	-1.347	29.70***	-8.851***	30.04***	-33.26***	-2.923
	(3.389)	(3.205)	(2.604)	(3.042)	(3.108)	(3.233)	(2.579)	(2.942)	(2.936)	(2.745)
Cohort 5	-19.35***	-42.12***	-40.41***	-0.399	-6.560*	31.65***	-8.625**	28.91***	-39.43***	-14.04***
	(3.802)	(3.581)	(3.149)	(3.466)	(3.233)	(3.573)	(2.827)	(3.543)	(3.323)	(2.854)
Cohort 6	-25.54***	-48.41***	-51.42***	-1.215	-12.50***	24.17***	-10.95***	22.35***	-47.31***	-15.18***
	(4.201)	(4.063)	(3.318)	(3.752)	(3.587)	(3.827)	(2.957)	(3.418)	(3.492)	(3.380)
Cohort 7	-40.41***	-63.82***	-63.55***	-13.51**	-22.04***	23.13***	-15.56***	23.55***	-66.44***	-33.34***
	(4.515)	(4.911)	(3.941)	(4.321)	(3.727)	(4.156)	(3.186)	(3.721)	(3.780)	(3.518)
Observations	7201	9198	10298	8392	8243	7557	7882	12358	7022	15524

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education, parental education, migrant status and gender not reported.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A20. Age and cohort effect on literacy skills – High education

	BE	CZ	DK	FI	IE	IT	NL	PL	SE	UK
Age: 30-36	-11.74*	-10.89*	-7.533	-1.624	-3.431	-6.798	-1.462	-2.973	-8.659	-1.197
	(4.885)	(5.438)	(4.222)	(4.817)	(2.945)	(6.008)	(3.189)	(3.239)	(4.768)	(3.791)
Age: 37-43	-14.85**	-21.22***	-19.64***	-4.468	-7.268*	-15.06*	-5.737	-1.202	-15.62**	-3.707
	(4.992)	(5.629)	(4.693)	(5.114)	(3.616)	(5.935)	(3.374)	(4.400)	(5.277)	(3.448)
Age: 44-50	-24.86***	-24.25***	-32.99***	-5.172	-23.80***	-12.10	-8.554*	-1.237	-25.24***	-17.52***
	(6.169)	(6.101)	(5.520)	(6.090)	(4.771)	(6.801)	(3.351)	(4.829)	(6.034)	(4.607)
Age: 51-57	-38.44***	-31.84***	-55.73***	-20.53**	-31.58***	-25.64**	-19.03***	-1.186	-44.00***	-29.78***
	(7.402)	(7.084)	(5.677)	(7.445)	(5.600)	(7.873)	(3.841)	(6.326)	(6.508)	(4.736)
Age: 58-65	-52.03***	-39.81***	-70.26***	-27.81***	-38.75***	-31.07***	-31.73***	-2.138	-57.39***	-42.47***
	(7.340)	(8.143)	(5.919)	(7.551)	(6.712)	(8.636)	(4.198)	(6.958)	(6.559)	(5.660)
Cohort 2	-7.103	-2.768	-10.62***	-6.081	-16.88*	-5.127	0.175	13.17	-29.74***	-0.602
	(7.324)	(4.658)	(2.913)	(4.645)	(7.033)	(6.032)	(4.066)	(7.430)	(6.318)	(5.088)
Cohort 3	-17.75**	1.433	-21.75***	0.401	-24.36***	2.463	-2.479	23.69**	-29.58***	-15.40**
	(6.742)	(5.859)	(3.142)	(5.473)	(6.683)	(6.976)	(3.824)	(7.209)	(5.537)	(5.112)
Cohort 4	-17.64*	-7.168	-32.10***	-6.542	-27.86***	-2.343	-3.100	30.46***	-31.64***	-17.56**
	(7.755)	(6.873)	(3.876)	(6.302)	(7.145)	(7.834)	(4.226)	(6.227)	(6.406)	(6.260)
Cohort 5	-24.52**	-9.719	-38.58***	1.836	-36.24***	-2.224	0.668	30.85***	-39.49***	-29.42***
	(8.584)	(7.171)	(4.603)	(7.276)	(7.311)	(7.804)	(4.760)	(7.604)	(6.716)	(6.119)
Cohort 6	-22.97*	-7.521	-52.58***	5.269	-43.99***	-4.244	1.982	31.14***	-42.57***	-35.91***
	(9.280)	(8.123)	(5.559)	(7.874)	(7.701)	(8.954)	(4.823)	(7.963)	(7.040)	(7.014)
Cohort 7	-32.17**	-25.30*	-58.36***	-1.223	-47.53***	-3.250	4.000	31.18***	-58.74***	-37.24***
	(10.727)	(9.851)	(7.396)	(8.833)	(8.309)	(10.151)	(5.066)	(8.294)	(7.864)	(7.436)
Observations	1938	1627	3353	1642	2311	1115	2220	2260	1785	4000

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A21. Age and cohort effect on literacy skills – Medium-low education

	BE	CZ	DK	FI	IE	IT	NL	PL	SE	UK
Age: 23-29	-6.624	-0.172	0.384	3.104	-4.486	-1.995	-1.151	-11.35***	-0.178	1.700
	(3.390)	(2.402)	(2.353)	(2.543)	(2.963)	(3.148)	(2.639)	(2.468)	(2.937)	(3.170)
Age: 30-36	-18.37***	-13.68***	-19.69***	-10.14***	-6.750*	-10.33**	-8.833**	-12.00***	-11.11***	-1.648
	(3.209)	(2.686)	(2.673)	(2.996)	(2.768)	(3.195)	(2.785)	(2.460)	(2.823)	(2.785)
Age: 37-43	-32.83***	-24.79***	-29.69***	-15.14***	-15.52***	-13.26***	-13.09***	-8.666**	-27.83***	-3.763
	(3.903)	(3.036)	(3.169)	(3.677)	(3.356)	(3.760)	(2.852)	(2.659)	(3.428)	(3.380)
Age: 44-50	-39.55***	-38.70***	-49.70***	-23.81***	-24.74***	-10.79*	-22.05***	-11.58***	-32.27***	-13.57***
	(4.064)	(3.781)	(3.320)	(4.170)	(3.661)	(4.191)	(3.247)	(3.313)	(3.719)	(3.411)
Age: 51-57	-52.11***	-48.07***	-67.49***	-30.94***	-24.25***	-5.299	-38.59***	0.581	-51.23***	-17.66***
	(4.315)	(3.916)	(3.791)	(4.630)	(3.973)	(4.427)	(3.628)	(3.367)	(3.878)	(3.922)
Age: 58-65	-60.08***	-58.07***	-81.61***	-44.62***	-33.10***	-17.25***	-47.80***	-5.737	-68.26***	-26.21***
	(4.502)	(4.381)	(4.291)	(4.868)	(4.079)	(4.903)	(3.782)	(3.300)	(3.974)	(3.951)
Cohort 2	5.413	-2.900	-9.030***	7.733***	11.88***	21.75***	-3.822	38.04***	-16.10***	20.03***
	(3.305)	(2.673)	(2.143)	(2.258)	(3.515)	(2.577)	(2.831)	(3.567)	(3.217)	(2.509)
Cohort 3	1.750	-14.56***	-20.15***	12.14***	11.28***	27.67***	-3.212	43.77***	-16.89***	10.36***
	(3.258)	(2.648)	(2.644)	(2.683)	(3.333)	(3.095)	(2.736)	(2.690)	(2.991)	(2.502)
Cohort 4	-2.913	-19.00***	-26.33***	16.68***	10.99**	35.35***	-5.592	51.14***	-27.48***	8.619**
	(4.123)	(3.429)	(3.201)	(3.532)	(3.754)	(3.700)	(3.116)	(3.154)	(3.303)	(3.065)
Cohort 5	-6.412	-28.49***	-43.69***	8.536*	8.948*	37.74***	-5.400	53.76***	-32.47***	4.763
	(4.588)	(3.722)	(3.920)	(4.089)	(3.909)	(4.119)	(3.467)	(3.810)	(3.896)	(3.686)
Cohort 6	-15.60**	-31.64***	-52.28***	8.675	5.456	34.37***	-7.792*	51.38***	-42.02***	2.905
	(4.851)	(4.395)	(3.906)	(4.684)	(4.245)	(4.406)	(3.738)	(3.689)	(4.136)	(4.058)
Cohort 7	-31.48***	-45.74***	-66.55***	-5.287	-5.865	26.80***	-16.82***	56.25***	-63.55***	-12.79**
	(5.188)	(5.143)	(4.359)	(5.259)	(4.521)	(4.847)	(4.029)	(4.013)	(4.447)	(4.351)
Observations	5189	7550	6941	6747	5855	6438	5632	9931	5213	11389

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A22. Age and cohort effect on Literacy skills - Medium educated

	BE	CZ	DK	IE	FI	IT	NL	PL	SE	UK
Age: 30-36	-22.35***	-21.34***	-29.17***	-6.348*	-14.96***	-13.69***	-13.02***	-23.81***	-15.58***	-1.560
	(3.359)	(3.510)	(3.116)	(2.736)	(3.388)	(3.384)	(3.075)	(2.753)	(3.206)	(3.221)
Age: 37-43	-38.43***	-36.90***	-38.65***	-15.26***	-24.46***	-15.25***	-18.37***	-26.32***	-29.43***	-7.578*
	(3.978)	(3.415)	(3.727)	(3.361)	(3.898)	(4.105)	(3.197)	(2.894)	(3.811)	(3.789)
Age: 44-50	-48.01***	-56.42***	-59.43***	-28.04***	-32.34***	-20.16***	-26.32***	-32.40***	-38.05***	-17.63***
	(4.184)	(4.512)	(4.010)	(4.171)	(4.407)	(4.270)	(3.688)	(3.649)	(4.012)	(4.029)
Age: 51-57	-67.30***	-73.56***	-76.35***	-34.12***	-42.57***	-24.68***	-46.97***	-36.08***	-58.28***	-27.04***
	(4.746)	(4.547)	(4.452)	(4.648)	(5.085)	(5.099)	(4.463)	(4.266)	(4.368)	(4.580)
Age: 58-65	-71.95***	-90.35***	-92.35***	-41.53***	-56.54***	-31.66***	-53.91***	-40.06***	-72.71***	-39.44***
	(4.883)	(5.245)	(4.856)	(5.036)	(5.350)	(5.513)	(4.661)	(3.989)	(4.540)	(4.943)
Cohort 2	-13.55**	-10.97***	-11.48***	-6.681	-1.770	-1.986	-12.50**	13.65**	-22.32***	-2.468
	(4.317)	(2.892)	(2.665)	(6.194)	(3.114)	(4.417)	(4.219)	(4.362)	(3.738)	(3.875)
Cohort 3	-12.61**	-28.01***	-22.26***	-13.27*	-0.961	-0.961	-10.40*	15.34***	-25.07***	-15.79***
	(4.147)	(3.263)	(3.264)	(5.915)	(3.573)	(4.298)	(4.120)	(3.849)	(3.468)	(4.545)
Cohort 4	-28.45***	-39.74***	-28.56***	-22.26***	-1.661	-0.0737	-13.65**	12.82**	-36.27***	-19.25***
	(4.831)	(4.217)	(3.657)	(6.192)	(4.366)	(4.998)	(4.235)	(4.141)	(3.738)	(4.373)
Cohort 5	-33.53***	-53.75***	-44.39***	-23.99***	-6.812	-4.848	-15.48***	9.979*	-42.11***	-27.80***
	(5.100)	(4.419)	(4.024)	(6.079)	(4.811)	(5.163)	(4.684)	(4.686)	(4.233)	(5.135)
Cohort 6	-43.67***	-60.19***	-52.48***	-29.83***	-12.15*	-11.55*	-21.36***	4.308	-54.47***	-32.08***
	(5.678)	(5.496)	(4.477)	(6.701)	(5.826)	(5.502)	(4.447)	(5.080)	(4.563)	(5.505)
Cohort 7	-58.84***	-76.57***	-65.36***	-45.11***	-21.70***	-22.60***	-28.43***	-1.881	-70.58***	-47.33***
	(5.840)	(6.158)	(4.724)	(6.628)	(6.052)	(5.654)	(4.709)	(5.331)	(5.036)	(5.895)
Observations	3298	5151	4416	3161	4849	3379	2880	6666	3688	5083

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A23. Age and cohort effect on Literacy skills – Low educated

	BE	CZ	DK	IE	FI	IT	NL	PL	SE	UK
Age: 30-36	-35.13***	-34.59***	-27.99***	-21.22***	-23.78**	-12.79*	-16.27***	-19.52**	-21.77**	-11.76*
	(7.929)	(9.542)	(5.109)	(5.008)	(8.797)	(5.388)	(4.890)	(6.911)	(7.047)	(4.835)
Age: 37-43	-47.90***	-53.92***	-38.16***	-26.09***	-17.18	-14.62*	-16.71***	-20.30*	-48.27***	-12.60*
	(9.454)	(12.241)	(6.298)	(5.898)	(9.857)	(6.253)	(4.960)	(8.398)	(8.220)	(5.861)
Age: 44-50	-49.23***	-76.07***	-53.58***	-35.61***	-26.36*	-4.416	-27.08***	-31.35***	-38.17***	-28.88***
	(9.379)	(12.802)	(6.621)	(5.976)	(10.587)	(6.835)	(5.459)	(9.234)	(8.797)	(5.808)
Age: 51-57	-60.19***	-82.83***	-66.82***	-30.95***	-30.74**	10.36	-40.78***	-7.301	-54.17***	-31.71***
	(9.467)	(12.839)	(7.463)	(6.302)	(10.892)	(6.989)	(5.422)	(8.224)	(8.697)	(6.303)
Age: 58-65	-68.13***	-91.44***	-76.58***	-40.34***	-40.24***	-1.257	-48.57***	-24.08**	-72.11***	-40.22***
	(9.731)	(12.823)	(7.681)	(6.300)	(11.302)	(7.757)	(5.651)	(8.428)	(8.989)	(6.328)
Cohort 2	10.44*	-0.0814	-7.345*	12.09**	6.179	25.48***	-1.014	36.44***	-16.34**	21.48***
	(4.968)	(6.610)	(3.668)	(4.455)	(4.097)	(3.219)	(3.619)	(6.219)	(5.376)	(3.622)
Cohort 3	0.477	-23.08**	-14.03**	10.72*	8.871	30.89***	-3.721	39.35***	-17.89**	5.992
	(5.231)	(7.287)	(4.326)	(4.415)	(6.056)	(4.113)	(3.618)	(5.460)	(5.696)	(3.644)
Cohort 4	1.563	-35.72***	-20.40***	12.63*	21.06*	46.04***	-8.386*	46.34***	-29.25***	3.616
	(7.118)	(10.049)	(6.036)	(5.297)	(9.166)	(5.055)	(4.189)	(6.636)	(6.479)	(4.611)
Cohort 5	-8.011	-50.68***	-39.05***	2.164	7.815	53.90***	-9.844*	54.24***	-35.38***	-4.835
	(8.402)	(12.162)	(7.138)	(5.809)	(10.373)	(5.803)	(4.677)	(8.113)	(8.240)	(5.616)
Cohort 6	-16.73	-63.70***	-44.79***	-4.781	19.94	49.02***	-11.54*	43.39***	-41.02***	-7.720
	(9.526)	(13.118)	(7.754)	(6.436)	(11.362)	(6.805)	(5.781)	(8.358)	(9.295)	(6.660)
Cohort 7	-32.37**	-76.64***	-59.55***	-8.470	0.992	51.41***	-19.10**	53.12***	-66.52***	-31.85***
	(10.205)	(13.836)	(8.283)	(7.285)	(11.833)	(7.657)	(5.971)	(8.714)	(9.636)	(6.550)
Observations	1891	2399	2525	2694	1898	3059	2752	3265	1525	6306

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A24. Age and cohort effect on literacy skills – Quantile regression – BE

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-9.374	-13.91***	-8.967**				-3.257	-9.481*	-3.465
	(4.834)	(3.662)	(3.268)				(6.465)	(3.786)	(3.865)
Age: 30-36	-31.42***	-25.04***	-19.95***	-14.24	-11.79	-7.892	-25.53***	-17.02***	-14.38**
	(5.386)	(3.192)	(3.494)	(8.343)	(6.245)	(9.271)	(6.877)	(3.481)	(4.631)
Age: 37-43	-41.54***	-37.49***	-27.68***	-20.35**	-14.85*	-10.16	-41.79***	-33.10***	-26.39***
	(5.871)	(3.976)	(4.580)	(7.054)	(6.927)	(9.861)	(8.456)	(4.720)	(5.452)
Age: 44-50	-47.19***	-48.46***	-40.08***	-25.95**	-23.99***	-23.19*	-40.64***	-43.27***	-35.21***
	(6.516)	(4.099)	(5.344)	(9.891)	(6.958)	(11.171)	(9.048)	(4.517)	(6.353)
Age: 51-57	-56.85***	-65.45***	-51.48***	-51.90***	-38.43***	-28.71*	-38.71***	-59.69***	-50.56***
	(7.145)	(4.185)	(6.496)	(11.914)	(8.885)	(11.619)	(9.668)	(5.292)	(6.824)
Age: 58-65	-66.75***	-74.84***	-59.52***	-68.18***	-47.29***	-47.77***	-51.39***	-69.77***	-56.13***
	(8.574)	(4.875)	(6.862)	(12.141)	(9.335)	(12.229)	(11.865)	(5.884)	(7.299)
Cohort 2	3.578	0.382	-5.358	-8.292	-2.591	-9.374	21.33*	6.010	-6.900
	(6.740)	(4.001)	(4.597)	(13.887)	(9.417)	(13.444)	(8.657)	(4.208)	(6.786)
Cohort 3	-2.315	-6.689	-13.06**	-21.20	-8.171	-20.51	16.15*	1.115	-9.328
	(6.058)	(3.963)	(4.137)	(13.032)	(9.618)	(11.252)	(7.553)	(4.283)	(5.508)
Cohort 4	-5.318	-13.66**	-16.12**	-25.68	-9.856	-20.15	21.08*	-8.071	-14.70*
	(7.299)	(4.305)	(4.999)	(15.086)	(10.759)	(13.135)	(8.498)	(4.978)	(6.657)
Cohort 5	-8.332	-22.30***	-24.61***	-32.46*	-16.56	-27.41*	23.17*	-12.00*	-20.94**
	(7.326)	(4.831)	(5.311)	(16.138)	(10.561)	(13.839)	(10.501)	(4.944)	(7.076)
Cohort 6	-9.455	-30.24***	-29.49***	-28.53	-14.23	-27.86*	16.97	-24.17***	-29.36***
	(7.626)	(5.190)	(5.535)	(16.450)	(12.913)	(13.247)	(10.116)	(5.877)	(7.690)
Cohort 7	-31.55***	-44.64***	-43.26***	-38.45*	-25.62	-35.16*	-5.671	-38.73***	-44.51***
	(8.787)	(5.273)	(7.119)	(18.478)	(13.860)	(15.030)	(11.224)	(6.108)	(8.271)
Observations	7201	7201	7201	1938	1938	1938	5189	5189	5189

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A25. Age and cohort effect on literacy skills – Quantile regression – CZ

	Overall population			**Highly educated**			**Low and medium educated**		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-6.166	-9.624**	-9.752*				-0.389	-1.067	-0.415
	(5.073)	(3.524)	(3.990)				(5.995)	(3.965)	(4.568)
Age: 30-36	-23.45***	-24.95***	-20.01***	-9.497	-11.23	-12.54	-15.66**	-13.92**	-12.75*
	(5.279)	(4.450)	(4.602)	(7.409)	(6.840)	(10.091)	(6.054)	(5.151)	(4.999)
Age: 37-43	-44.86***	-39.13***	-34.51***	-29.35**	-20.09**	-18.66	-27.02***	-24.98***	-22.33***
	(7.117)	(4.455)	(5.358)	(10.092)	(7.341)	(10.522)	(8.013)	(5.711)	(4.645)
Age: 44-50	-57.83***	-55.06***	-47.73***	-23.74*	-22.74**	-23.52	-40.37***	-38.99***	-38.45***
	(7.851)	(5.707)	(6.443)	(12.063)	(8.421)	(13.898)	(8.625)	(6.559)	(6.292)
Age: 51-57	-72.85***	-67.94***	-60.19***	-28.83*	-34.56***	-27.05	-48.85***	-47.60***	-47.14***
	(8.801)	(6.282)	(7.172)	(12.609)	(8.966)	(15.294)	(9.912)	(7.018)	(6.589)
Age: 58-65	-88.25***	-79.86***	-71.87***	-33.52*	-39.62***	-42.36**	-61.75***	-56.24***	-57.43***
	(9.336)	(6.036)	(7.483)	(16.141)	(7.618)	(16.372)	(11.392)	(6.983)	(6.377)
Cohort 2	-8.927	-6.495*	-9.649*	-0.715	-2.516	-4.514	0.525	-2.758	-5.494
	(5.216)	(3.056)	(4.131)	(9.235)	(5.805)	(8.879)	(6.758)	(3.683)	(4.135)
Cohort 3	-20.49***	-20.08***	-20.37***	10.84	0.870	-1.511	-11.52	-13.76**	-17.64***
	(5.590)	(3.870)	(4.751)	(11.305)	(7.532)	(12.973)	(5.925)	(4.327)	(4.787)
Cohort 4	-33.26***	-30.16***	-31.17***	-2.277	-6.054	-8.066	-15.01	-18.72***	-23.11***
	(8.240)	(4.616)	(5.674)	(13.267)	(6.544)	(14.818)	(9.831)	(5.040)	(5.815)
Cohort 5	-45.42***	-40.30***	-36.56***	-4.834	-9.004	-9.507	-26.99**	-27.20***	-30.65***
	(9.107)	(5.419)	(6.782)	(16.318)	(8.428)	(15.817)	(8.590)	(5.732)	(6.146)
Cohort 6	-53.04***	-45.98***	-43.29***	-5.127	-8.369	-3.231	-29.44**	-30.34***	-34.28***
	(9.472)	(5.421)	(7.024)	(15.349)	(9.551)	(16.115)	(10.454)	(6.595)	(6.694)
Cohort 7	-73.92***	-59.65***	-53.91***	-18.62	-24.20*	-28.97	-48.69***	-42.69***	-44.63***
	(10.968)	(6.589)	(8.413)	(16.373)	(11.408)	(19.369)	(11.957)	(7.693)	(8.312)
Observations	9198	9198	9198	1627	1627	1627	7550	7550	7550

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A26. Age and cohort effect on literacy skills – Quantile regression – DK

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-21.47***	-12.66***	-6.448				-1.586	2.036	3.324
	(4.674)	(2.866)	(3.387)				(5.752)	(2.905)	(4.490)
Age: 30-36	-40.70***	-28.55***	-20.11***	-10.69	-6.936	-5.999	-28.56***	-17.63***	-14.07***
	(5.020)	(2.946)	(3.729)	(8.711)	(6.146)	(7.248)	(7.475)	(3.887)	(4.190)
Age: 37-43	-58.66***	-38.64***	-26.72***	-27.16**	-20.42***	-12.81	-46.34***	-25.07***	-20.66***
	(6.256)	(3.266)	(4.993)	(9.201)	(5.612)	(7.120)	(8.519)	(3.876)	(4.970)
Age: 44-50	-81.11***	-52.86***	-42.85***	-39.27***	-31.28***	-29.58**	-73.55***	-42.92***	-36.98***
	(6.244)	(3.691)	(5.562)	(11.336)	(6.871)	(9.017)	(8.794)	(4.314)	(4.859)
Age: 51-57	-98.83***	-73.25***	-57.10***	-69.47***	-54.71***	-44.66***	-88.75***	-63.36***	-53.65***
	(7.318)	(4.073)	(6.259)	(11.205)	(7.264)	(9.362)	(9.572)	(4.748)	(5.931)
Age: 58-65	-115.0***	-86.29***	-69.67***	-87.22***	-69.20***	-58.40***	-105.7***	-76.51***	-66.61***
	(7.520)	(4.337)	(7.271)	(12.089)	(6.988)	(9.879)	(9.891)	(5.156)	(6.890)
Cohort 2	-9.346**	-10.93***	-9.360**	-8.558	-11.52**	-10.73*	-8.693	-8.711**	-9.485**
	(3.467)	(2.265)	(3.065)	(5.390)	(3.506)	(4.325)	(4.608)	(2.804)	(3.551)
Cohort 3	-21.71***	-19.43***	-16.84***	-21.92**	-23.15***	-21.44***	-24.68***	-18.99***	-16.36***
	(4.705)	(2.609)	(3.996)	(7.203)	(4.308)	(5.383)	(5.982)	(3.279)	(4.830)
Cohort 4	-33.48***	-26.47***	-24.00***	-33.31***	-32.21***	-30.98***	-36.50***	-22.90***	-23.01***
	(5.784)	(3.212)	(4.811)	(8.554)	(4.860)	(7.494)	(7.206)	(3.925)	(5.269)
Cohort 5	-46.91***	-39.37***	-35.18***	-39.93***	-38.52***	-37.23***	-56.06***	-40.51***	-37.87***
	(6.393)	(3.520)	(5.180)	(9.452)	(5.787)	(7.486)	(8.222)	(4.202)	(6.821)
Cohort 6	-67.66***	-47.74***	-39.07***	-60.45***	-51.62***	-44.61***	-72.05***	-46.75***	-39.99***
	(7.200)	(4.103)	(5.558)	(11.320)	(6.803)	(9.552)	(8.868)	(4.844)	(6.270)
Cohort 7	-82.76***	-60.72***	-50.85***	-70.43***	-57.39***	-47.18***	-90.15***	-61.28***	-53.68***
	(8.678)	(4.658)	(6.587)	(14.069)	(10.271)	(10.881)	(10.108)	(5.063)	(6.739)
Observations	10298	10298	10298	3353	3353	3353	6941	6941	6941

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Table A27. Age and cohort effect on literacy skills – Quantile regression – FI

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-11.67**	-7.333**	-5.706				1.936	3.149	4.356
	(4.352)	(2.399)	(3.320)				(5.068)	(3.115)	(3.687)
Age: 30-36	-27.18***	-18.62***	-12.18**	-2.560	-1.452	3.163	-17.00**	-9.509*	-3.380
	(4.956)	(3.188)	(4.247)	(11.329)	(6.121)	(9.909)	(6.508)	(3.909)	(5.005)
Age: 37-43	-37.84***	-25.51***	-16.78***	-11.57	-6.913	-2.126	-23.72***	-15.05**	-7.144
	(6.079)	(4.155)	(4.633)	(10.458)	(7.080)	(9.624)	(6.978)	(4.648)	(5.801)
Age: 44-50	-49.46***	-31.59***	-19.68***	-6.916	-5.198	2.949	-37.64***	-23.05***	-10.68
	(6.753)	(4.573)	(4.978)	(10.745)	(7.606)	(10.333)	(7.807)	(5.394)	(6.509)
Age: 51-57	-63.26***	-40.99***	-26.50***	-33.13**	-23.43*	-3.569	-45.89***	-30.20***	-16.68*
	(7.959)	(5.125)	(5.076)	(12.861)	(9.899)	(12.774)	(8.743)	(6.027)	(6.932)
Age: 58-65	-71.86***	-54.14***	-38.23***	-41.75**	-26.93**	-11.95	-54.25***	-45.30***	-31.45***
	(8.010)	(5.637)	(5.397)	(14.736)	(9.582)	(13.882)	(8.915)	(6.657)	(6.764)
Cohort 2	0.662	0.387	1.920	-12.80	-9.199	2.899	13.37*	6.313*	5.025
	(4.898)	(2.159)	(2.936)	(8.947)	(6.366)	(7.500)	(5.756)	(2.836)	(3.398)
Cohort 3	2.396	3.846	6.230	-4.492	0.336	11.96	18.49**	12.39***	9.918*
	(5.979)	(3.182)	(3.907)	(10.594)	(8.016)	(8.351)	(6.458)	(3.604)	(4.063)
Cohort 4	-0.887	2.571	10.15*	-17.25	-7.259	12.37	25.11***	14.19**	16.37***
	(7.350)	(3.990)	(4.139)	(12.175)	(8.725)	(10.412)	(7.610)	(4.815)	(4.692)
Cohort 5	-9.417	0.0677	9.649	-9.350	0.890	20.05	9.049	8.522	14.78*
	(6.851)	(4.768)	(4.996)	(12.812)	(10.096)	(12.553)	(7.456)	(5.737)	(5.959)
Cohort 6	-11.52	-1.560	9.867	-9.685	1.188	24.00	11.25	8.015	11.73
	(8.275)	(5.411)	(5.124)	(14.237)	(10.896)	(12.952)	(8.628)	(6.482)	(7.010)
Cohort 7	-27.82***	-14.04*	-1.396	-19.42	-1.817	20.79	-7.489	-6.109	0.253
	(8.031)	(5.808)	(6.360)	(18.186)	(11.312)	(16.078)	(9.345)	(6.740)	(8.084)
Observations	8392	8392	8392	1642	1642	1642	6747	6747	6747

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A28. Age and cohort effect on Literacy skills – Quantile regression – IE

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-7.115	-7.076*	-10.14**				0.618	-3.411	-5.072
	(5.110)	(2.884)	(3.698)				(8.133)	(4.129)	(5.023)
Age: 30-36	-11.26*	-9.557***	-12.11**	-4.638	-0.585	-3.866	-10.28	-4.526	-5.604
	(4.454)	(2.548)	(3.795)	(7.589)	(4.184)	(6.539)	(6.769)	(3.664)	(4.829)
Age: 37-43	-15.66**	-16.48***	-20.67***	-9.112	-4.434	-8.295	-16.69	-13.05***	-16.24**
	(5.608)	(3.036)	(4.210)	(7.952)	(4.959)	(8.425)	(8.768)	(3.860)	(5.488)
Age: 44-50	-32.47***	-27.48***	-30.76***	-28.42*	-20.61**	-20.35*	-24.42*	-23.07***	-24.17***
	(6.119)	(3.517)	(4.430)	(12.602)	(6.924)	(10.146)	(9.500)	(4.702)	(5.841)
Age: 51-57	-28.50***	-27.91***	-39.22***	-31.76*	-26.54***	-37.03**	-16.62	-22.64***	-32.94***
	(7.613)	(4.673)	(5.681)	(15.873)	(7.955)	(11.372)	(9.227)	(5.155)	(7.279)
Age: 58-65	-35.41***	-37.60***	-47.50***	-38.05*	-35.46***	-43.61***	-26.43*	-32.24***	-42.32***
	(7.123)	(5.003)	(5.453)	(15.684)	(8.259)	(11.226)	(10.312)	(5.324)	(6.408)
Cohort 2	13.34*	6.879	-3.169	-11.94	-10.41	-24.30	21.21*	15.86***	-1.658
	(6.268)	(4.132)	(5.244)	(19.144)	(12.883)	(14.443)	(8.301)	(4.590)	(6.523)
Cohort 3	9.003	2.711	-8.552	-24.45	-15.57	-29.59*	28.38**	12.30**	-3.375
	(6.235)	(4.019)	(4.936)	(16.496)	(11.403)	(14.871)	(9.266)	(4.253)	(5.560)
Cohort 4	10.88	-1.843	-15.72**	-26.96	-20.23	-33.02*	31.39**	12.97*	-11.60
	(6.533)	(5.044)	(4.940)	(16.384)	(11.532)	(16.014)	(11.057)	(5.154)	(6.032)
Cohort 5	1.700	-6.317	-20.01***	-31.90	-29.59*	-45.10**	28.46**	10.79	-10.94
	(7.873)	(4.777)	(5.829)	(18.927)	(12.633)	(15.525)	(10.459)	(5.746)	(6.468)
Cohort 6	0.157	-10.86	-28.95***	-42.06*	-36.57**	-51.76**	29.29*	8.482	-18.40*
	(8.098)	(5.558)	(5.392)	(18.613)	(12.478)	(16.509)	(11.893)	(5.231)	(7.189)
Cohort 7	-9.684	-21.26***	-38.95***	-42.14*	-38.44**	-58.18***	18.12	-4.586	-32.11***
	(8.427)	(5.868)	(6.082)	(19.692)	(13.316)	(14.969)	(11.611)	(6.085)	(7.658)
Observations	8243	8243	8243	2311	2311	2311	5855	5855	5855

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A29. Age and cohort effect on Literacy skills – Quantile regression – IT

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-11.43	-14.59***	-12.27**				-2.022	-3.237	2.475
	(6.084)	(3.644)	(4.332)				(8.629)	(4.093)	(4.943)
Age: 30-36	-13.23*	-18.88***	-20.40***	-13.30	-3.842	-4.306	-3.670	-10.86**	-12.87**
	(6.319)	(3.754)	(4.272)	(12.827)	(7.940)	(9.582)	(8.341)	(4.055)	(4.469)
Age: 37-43	-11.72	-23.06***	-24.50***	-14.33	-17.85*	-10.98	-1.286	-16.07**	-15.85**
	(7.084)	(4.527)	(4.641)	(12.099)	(7.832)	(11.619)	(10.079)	(4.955)	(5.677)
Age: 44-50	-6.040	-20.43***	-26.48***	-17.62	-11.96	-11.58	9.901	-13.75**	-20.29***
	(7.334)	(4.433)	(5.858)	(15.662)	(9.601)	(13.159)	(11.400)	(5.205)	(6.144)
Age: 51-57	8.653	-15.96**	-26.13***	-30.07	-24.70*	-18.92	30.81*	-12.15*	-25.69***
	(8.431)	(5.274)	(5.910)	(17.336)	(10.354)	(14.512)	(13.550)	(5.846)	(6.715)
Age: 58-65	2.512	-27.80***	-36.47***	-45.54*	-29.37*	-20.54	24.83	-27.40***	-36.52***
	(9.472)	(5.246)	(6.728)	(19.005)	(12.524)	(15.981)	(14.575)	(6.120)	(7.254)
Cohort 2	29.53***	17.42***	5.023	-1.584	-5.659	-0.682	39.07***	21.39***	7.155
	(5.688)	(3.557)	(4.288)	(15.651)	(8.392)	(8.740)	(7.570)	(4.468)	(4.276)
Cohort 3	38.43***	19.40***	6.861	-0.496	2.672	9.567	54.74***	23.29***	8.968*
	(7.486)	(4.542)	(4.749)	(16.534)	(10.426)	(12.597)	(8.685)	(4.741)	(4.570)
Cohort 4	56.39***	24.43***	8.616	-3.653	-2.594	8.106	77.10***	28.03***	7.723
	(8.202)	(4.121)	(5.039)	(21.261)	(11.874)	(15.621)	(12.010)	(5.437)	(5.408)
Cohort 5	59.74***	25.52***	6.137	-3.121	-4.100	5.863	86.90***	30.24***	4.438
	(9.266)	(4.643)	(5.605)	(19.981)	(11.670)	(13.858)	(11.854)	(5.718)	(5.757)
Cohort 6	51.53***	17.49***	0.189	-3.621	-7.874	3.937	87.86***	23.97***	2.992
	(8.897)	(4.766)	(6.543)	(23.812)	(13.291)	(15.730)	(13.055)	(6.140)	(6.856)
Cohort 7	53.73***	15.48**	-4.836	0.0204	-2.691	-2.307	84.90***	16.62**	-9.413
	(9.435)	(5.387)	(6.586)	(25.170)	(15.209)	(21.010)	(14.339)	(6.344)	(7.545)
Observations	7557	7557	7557	1115	1115	1115	6438	6438	6438

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A30. Age and cohort effect on Literacy skills – Quantile regression – NL

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-11.60**	-6.071*	-2.697				-3.207	-1.380	0.596
	(4.037)	(2.794)	(3.204)				(5.820)	(3.232)	(4.600)
Age: 30-36	-17.06***	-9.993***	-6.329	-1.491	-0.121	-3.154	-12.54	-8.587*	-4.961
	(4.542)	(2.957)	(3.861)	(7.234)	(4.855)	(6.518)	(7.406)	(4.029)	(4.897)
Age: 37-43	-25.24***	-14.02***	-8.393*	-6.819	-4.143	-7.485	-21.25**	-11.25**	-5.929
	(4.441)	(2.893)	(3.940)	(7.198)	(4.721)	(6.725)	(7.039)	(4.204)	(5.507)
Age: 44-50	-33.49***	-22.35***	-13.53**	-13.18	-7.601	-8.128	-32.62***	-20.67***	-11.21*
	(5.059)	(3.492)	(4.340)	(7.393)	(4.881)	(7.314)	(7.782)	(4.240)	(5.494)
Age: 51-57	-57.40***	-36.73***	-23.84***	-33.71***	-17.24**	-15.48*	-51.93***	-38.07***	-24.93***
	(5.387)	(3.595)	(5.345)	(7.719)	(5.721)	(7.425)	(8.415)	(5.045)	(6.661)
Age: 58-65	-64.33***	-45.89***	-31.66***	-45.21***	-31.23***	-25.79***	-59.74***	-47.24***	-32.70***
	(5.567)	(3.954)	(5.278)	(8.514)	(6.105)	(7.803)	(8.425)	(4.769)	(6.650)
Cohort 2	-4.462	-5.013	-2.111	-4.840	0.729	4.427	-1.514	-4.564	-4.915
	(4.454)	(2.966)	(4.105)	(8.719)	(5.375)	(8.057)	(7.542)	(3.971)	(4.912)
Cohort 3	-8.148	-4.938	-0.874	-10.27	-0.717	0.512	-3.800	-4.484	-0.0231
	(4.213)	(2.591)	(4.062)	(8.264)	(5.088)	(7.551)	(6.813)	(3.589)	(4.314)
Cohort 4	-15.83***	-7.240*	-1.825	-10.85	-1.453	-0.110	-10.56	-4.427	1.189
	(4.681)	(3.137)	(4.580)	(8.512)	(5.699)	(7.683)	(7.544)	(3.731)	(5.192)
Cohort 5	-13.47**	-7.863*	-2.231	-9.748	1.902	6.761	-5.368	-5.390	-0.531
	(4.985)	(3.316)	(5.068)	(8.713)	(5.458)	(8.975)	(8.169)	(4.162)	(5.855)
Cohort 6	-18.94***	-10.46**	-0.181	-11.89	4.775	8.194	-11.08	-9.060*	2.244
	(5.206)	(3.245)	(5.517)	(10.034)	(5.960)	(8.907)	(9.087)	(4.448)	(6.232)
Cohort 7	-29.05***	-14.30***	-3.448	-6.508	6.339	10.58	-25.86**	-17.09***	-4.707
	(5.348)	(3.890)	(6.462)	(10.393)	(6.268)	(9.584)	(9.928)	(4.786)	(8.054)
Observations	7882	7882	7882	2220	2220	2220	5632	5632	5632

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A31. Age and cohort effect on Literacy skills – Quantile regression – PL

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-25.88***	-24.82***	-17.66***				-15.12**	-11.81***	-6.521
	(4.558)	(2.524)	(3.090)				(5.394)	(3.187)	(3.656)
Age: 30-36	-30.81***	-28.50***	-22.73***	-1.964	-2.311	-4.942	-14.39*	-14.50***	-10.39**
	(4.625)	(3.246)	(3.389)	(8.503)	(4.619)	(7.537)	(5.880)	(3.740)	(3.956)
Age: 37-43	-31.03***	-31.98***	-22.60***	-0.238	-3.358	-0.618	-4.671	-12.94***	-8.989
	(4.989)	(3.894)	(4.263)	(12.308)	(7.023)	(10.718)	(6.489)	(3.765)	(4.844)
Age: 44-50	-37.96***	-38.16***	-27.35***	4.642	-4.210	-3.052	-5.015	-16.70***	-9.977
	(5.702)	(5.262)	(4.976)	(12.920)	(7.040)	(12.564)	(7.060)	(4.500)	(5.423)
Age: 51-57	-33.72***	-33.38***	-24.64***	2.368	-0.181	-4.715	9.390	-6.096	-3.516
	(6.872)	(4.763)	(5.722)	(13.911)	(7.890)	(11.004)	(8.119)	(4.983)	(6.759)
Age: 58-65	-39.84***	-42.81***	-27.92***	-6.324	-2.651	-5.811	9.105	-13.70*	-5.559
	(6.436)	(5.300)	(5.892)	(14.901)	(8.412)	(12.403)	(9.182)	(5.492)	(6.008)
Cohort 2	29.58***	24.52***	16.89**	9.715	13.60	17.72	46.77***	39.12***	23.66***
	(6.494)	(4.492)	(5.492)	(16.229)	(9.187)	(11.152)	(7.414)	(4.838)	(6.421)
Cohort 3	32.27***	28.40***	19.01***	21.71	20.84**	25.06*	55.08***	44.33***	26.69***
	(5.678)	(3.337)	(4.555)	(15.183)	(7.550)	(10.184)	(6.758)	(4.194)	(5.149)
Cohort 4	37.19***	29.15***	20.37***	26.48	28.22***	28.87*	70.39***	49.76***	30.53***
	(6.657)	(4.319)	(5.991)	(15.746)	(7.935)	(11.734)	(8.509)	(4.851)	(7.352)
Cohort 5	32.51***	28.00***	23.31***	22.76	31.58***	33.10*	74.32***	50.93***	34.69***
	(7.698)	(5.090)	(6.046)	(16.836)	(8.985)	(13.129)	(11.259)	(5.204)	(6.607)
Cohort 6	27.12***	20.98***	16.56**	29.01	26.83**	32.41*	72.84***	48.86***	29.93***
	(7.550)	(4.985)	(6.024)	(18.256)	(8.710)	(13.070)	(10.041)	(6.040)	(7.605)
Cohort 7	29.10***	20.94***	18.87**	29.92	26.17**	32.05*	81.72***	51.48***	33.84***
	(7.769)	(5.566)	(6.460)	(21.252)	(9.031)	(14.102)	(11.722)	(6.556)	(7.916)
Observations	12358	12358	12358	2260	2260	2260	9931	9931	9931

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A32. Age and cohort effect on Literacy skills – Quantile regression – SE

	Overall population			Highly educated			Low and medium educated		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Age: 23-29	-11.26*	-4.871	-0.830				-3.420	1.525	3.232
	(5.693)	(2.803)	(4.100)				(6.179)	(3.890)	(4.651)
Age: 30-36	-19.17***	-15.64***	-13.56**	-12.35	-8.641	-9.059	-14.43*	-8.913*	-7.903
	(5.226)	(2.694)	(4.238)	(7.988)	(4.983)	(9.381)	(5.885)	(3.925)	(5.487)
Age: 37-43	-28.50***	-29.69***	-32.80***	-12.17	-16.80**	-16.66	-23.13***	-27.39***	-29.93***
	(5.750)	(3.788)	(4.465)	(11.264)	(6.349)	(10.094)	(6.910)	(4.607)	(5.634)
Age: 44-50	-39.06***	-36.13***	-38.51***	-22.33	-27.54***	-27.02*	-35.22***	-32.07***	-34.65***
	(6.352)	(3.975)	(4.769)	(12.141)	(7.440)	(11.071)	(7.067)	(4.922)	(7.370)
Age: 51-57	-47.97***	-56.76***	-64.19***	-36.75*	-46.65***	-53.66***	-40.82***	-54.12***	-59.57***
	(7.237)	(4.008)	(5.620)	(14.566)	(8.617)	(11.615)	(8.723)	(5.077)	(7.147)
Age: 58-65	-68.97***	-72.62***	-78.11***	-51.79***	-61.48***	-63.60***	-63.03***	-71.28***	-75.78***
	(7.059)	(3.976)	(5.343)	(13.966)	(8.514)	(12.844)	(8.604)	(5.107)	(7.444)
Cohort 2	-14.20*	-21.40***	-30.86***	-26.81*	-30.45***	-34.20***	-7.334	-15.94***	-27.44***
	(6.066)	(3.548)	(5.419)	(12.887)	(8.017)	(10.174)	(7.247)	(4.109)	(5.465)
Cohort 3	-18.34**	-24.63***	-31.47***	-23.60	-31.36***	-30.65***	-11.97	-16.40***	-26.26***
	(5.829)	(3.369)	(3.995)	(12.093)	(6.676)	(8.870)	(7.513)	(4.000)	(4.777)
Cohort 4	-23.25***	-34.05***	-44.30***	-21.10	-33.57***	-38.23***	-14.82*	-29.62***	-41.89***
	(5.820)	(3.640)	(4.974)	(12.669)	(7.753)	(10.916)	(7.189)	(4.283)	(5.512)
Cohort 5	-27.30***	-41.18***	-53.20***	-28.40*	-43.54***	-48.61***	-19.22*	-34.36***	-47.50***
	(6.849)	(4.151)	(6.064)	(14.291)	(8.447)	(11.363)	(8.906)	(4.834)	(6.674)
Cohort 6	-35.85***	-48.19***	-58.94***	-28.96	-46.98***	-54.07***	-27.58**	-43.98***	-55.30***
	(7.498)	(4.413)	(5.786)	(15.184)	(9.608)	(10.284)	(9.638)	(4.848)	(7.138)
Cohort 7	-50.58***	-66.29***	-85.78***	-42.30*	-63.01***	-66.11***	-46.37***	-64.55***	-84.94***
	(7.584)	(4.600)	(6.539)	(17.016)	(10.479)	(11.786)	(9.335)	(5.297)	(7.496)
Observations	7022	7022	7022	1785	1785	1785	5213	5213	5213

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A33. Age and cohort effect on Literacy skills – Quantile regression – UK

	Overall population			Highly educated			Low and medium educated		
	10th	**50th**	**90th**	**10th**	**50th**	**90th**	**10th**	**50th**	**90th**
Age: 23-29	7.417	1.514	4.203				6.080	0.974	3.807
	(6.199)	(3.776)	(3.837)				(6.531)	(4.704)	(4.856)
Age: 30-36	9.881	-11.32**	-7.440	3.459	-2.848	-7.305	13.10	-7.582	-2.209
	(5.830)	(3.546)	(4.067)	(9.931)	(4.957)	(9.227)	(7.937)	(4.282)	(4.762)
Age: 37-43	7.465	-13.37**	-11.92*	8.736	-7.156	-10.04	8.040	-9.608*	-5.123
	(6.679)	(4.283)	(5.460)	(11.025)	(5.176)	(6.285)	(9.049)	(4.800)	(6.811)
Age: 44-50	-0.377	-28.62***	-27.05***	-23.03	-18.40**	-16.80	7.273	-22.79***	-21.38***
	(7.839)	(4.398)	(4.917)	(13.867)	(6.210)	(9.013)	(10.764)	(4.993)	(6.081)
Age: 51-57	-12.74	-37.64***	-37.31***	-28.88*	-33.60***	-30.81***	3.762	-28.17***	-25.42**
	(8.679)	(4.846)	(5.594)	(13.217)	(7.426)	(9.034)	(10.502)	(5.595)	(8.244)
Age: 58-65	-20.71*	-49.01***	-48.69***	-51.01**	-45.20***	-42.84***	-1.043	-38.63***	-37.70***
	(9.015)	(4.866)	(6.028)	(17.050)	(8.694)	(11.881)	(12.539)	(5.564)	(7.602)
Cohort 2	21.52***	9.494**	6.429	-2.359	-0.113	-0.349	37.92***	14.85***	12.51*
	(5.373)	(3.292)	(4.258)	(13.853)	(8.573)	(12.348)	(6.373)	(3.652)	(5.161)
Cohort 3	8.369	-5.732	-7.278	-24.98	-15.04*	-13.25	28.28***	4.131	-0.369
	(5.815)	(3.255)	(4.568)	(15.732)	(6.603)	(12.130)	(7.371)	(3.806)	(5.089)
Cohort 4	4.742	-8.214	-13.23**	-20.03	-19.35*	-17.51	26.62**	1.390	-3.064
	(7.164)	(4.302)	(4.222)	(15.810)	(8.842)	(13.791)	(8.543)	(4.808)	(6.420)
Cohort 5	3.687	-22.78***	-28.73***	-38.57*	-30.72***	-30.94	34.57**	-6.659	-14.88*
	(7.829)	(4.455)	(5.844)	(17.010)	(8.720)	(16.175)	(10.663)	(5.271)	(5.965)
Cohort 6	-0.352	-24.53***	-24.84***	-44.13**	-36.31***	-29.74	28.84*	-10.27	-10.22
	(9.605)	(4.733)	(5.137)	(16.609)	(10.421)	(16.972)	(12.103)	(5.910)	(7.355)
Cohort 7	-2.843	-46.13***	-52.65***	-34.83	-41.95***	-38.61*	29.05*	-29.59***	-36.39***
	(9.450)	(5.004)	(6.019)	(20.453)	(10.831)	(16.023)	(14.334)	(6.087)	(8.306)
Observations	15524	15524	15524	4000	4000	4000	11389	11389	11389

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education (columns 1-3), parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A34. Age and cohort effect on Literacy skills – Interaction with ALL

	BE	CZ	DK	FI	IE	IT	NL	PL	SE	UK
Age: 30-36	-5.171	-5.942	-1.325	0.673	-0.312	-0.870	-4.475	2.423	-2.587	-1.456
	(4.162)	(3.544)	(3.721)	(4.773)	(3.364)	(3.346)	(3.895)	(3.286)	(4.821)	(3.025)
Age: 37-43	-18.05***	-22.23***	-15.29***	-7.860	-6.247	-4.008	-6.637	2.816	-19.81***	-2.795
	(3.943)	(3.692)	(3.839)	(4.607)	(3.546)	(3.375)	(3.835)	(3.471)	(4.454)	(2.970)
Age: 44-50	-23.97***	-34.14***	-29.03***	-15.32***	-18.58***	-2.381	-18.17***	1.263	-27.17***	-14.34***
	(4.031)	(4.350)	(3.854)	(4.506)	(3.630)	(3.966)	(3.661)	(3.576)	(4.837)	(3.104)
Age: 51-57	-35.89***	-45.21***	-49.52***	-23.23***	-17.44***	2.083	-33.27***	11.76**	-42.85***	-13.90***
	(4.321)	(4.264)	(4.326)	(4.746)	(4.589)	(4.303)	(3.952)	(4.049)	(4.861)	(3.647)
Age: 58-65	-41.95***	-52.37***	-58.34***	-30.54***	-25.02***	-8.264	-43.00***	6.824	-56.77***	-18.42***
	(4.196)	(4.365)	(4.598)	(4.854)	(4.370)	(4.557)	(3.837)	(3.948)	(4.604)	(3.265)
ALL	18.21***	10.34**	21.95***	22.85***	19.22***	22.40***	11.21**	21.10***	9.847*	26.08***
	(4.755)	(3.540)	(3.429)	(4.061)	(4.025)	(4.381)	(3.916)	(3.951)	(4.469)	(3.146)
Age 30-36*ALL	0.234	2.959	-5.933	-0.125	3.666	-3.920	3.965	-7.244	0.180	4.216
	(5.743)	(4.416)	(4.209)	(5.205)	(4.861)	(5.490)	(4.748)	(4.991)	(5.247)	(3.800)
Age 37-43*ALL	4.870	3.525	-2.060	0.721	5.012	-0.496	1.022	-0.774	12.46*	2.111
	(5.845)	(4.775)	(4.177)	(5.058)	(4.856)	(5.423)	(4.943)	(5.536)	(5.148)	(4.066)
Age 44-50*ALL	3.292	2.886	-2.826	4.842	4.232	1.100	4.608	-0.000443	9.282	6.600
	(5.764)	(4.521)	(3.989)	(4.722)	(4.869)	(5.703)	(4.680)	(5.406)	(5.274)	(3.745)
Age 51-57*ALL	3.283	3.705	0.846	4.741	-0.0210	-0.0275	9.393*	-0.111	9.223	0.623
	(5.783)	(4.648)	(4.103)	(5.055)	(5.648)	(6.088)	(4.605)	(5.577)	(5.883)	(4.031)
Age 58-65*ALL	2.792	1.287	-0.645	-0.432	0.775	12.97	7.421	3.438	9.972	-4.009
	(6.001)	(5.160)	(4.148)	(5.187)	(5.882)	(7.254)	(4.679)	(7.131)	(5.382)	(4.049)
Cohort 2	6.993*	-5.908*	-9.110***	4.261*	11.32***	20.02***	-1.675	35.03***	-14.52***	20.44***
	(3.102)	(2.405)	(1.828)	(2.084)	(3.088)	(2.376)	(2.478)	(3.530)	(2.912)	(2.152)
Cohort 3	3.491	-14.67***	-17.71***	9.238***	6.266*	25.24***	-5.649*	39.64***	-18.76***	9.044***
	(2.971)	(2.538)	(2.143)	(2.511)	(3.048)	(2.861)	(2.585)	(2.875)	(2.618)	(2.072)
Cohort 4	1.153	-25.49***	-25.34***	8.749**	7.094*	31.75***	-7.488*	46.03***	-24.69***	8.123**
	(3.787)	(3.422)	(2.771)	(3.201)	(3.336)	(3.441)	(2.924)	(3.442)	(3.011)	(2.623)
Cohort 5	0.295	-31.52***	-32.87***	10.88**	4.330	33.43***	-5.655	47.93***	-28.22***	5.255
	(4.009)	(3.469)	(3.260)	(3.511)	(3.412)	(3.663)	(3.129)	(4.175)	(3.415)	(2.741)
Cohort 6	-12.22**	-37.98***	-45.95***	8.560*	-2.072	33.14***	-10.81***	51.71***	-43.42***	0.557
	(4.688)	(4.206)	(3.921)	(4.100)	(3.689)	(4.060)	(3.258)	(4.036)	(3.686)	(3.181)
Observations	5476	7087	8563	6800	6912	6454	6555	6571	5615	13119

Notes: Own elaborations on IALS and PIAAC data. All figures are weighted. Controls for education, parental education, migrant status and gender not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table A35. Complete list of NACE codes

NACE code	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage; waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transporting and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other services activities
T	Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

Table A36. Summary statistics for the change in employment shares across EU countries, by main economic sector

Main economic sector	Observations	Mean	Standard deviation	Min	Max
Industry (NACE B-E)	467	-0.33	0.51	-2.4	4.1
Manufacturing (NACE C)	449	-0.30	0.47	-2.4	3.6
Construction (NACE F)	467	-0.02	0.50	-3.2	2.5
New sectors (NACE J, M-N)	467	0.29	0.32	-1.0	1.8
Finance & estate (NACE K, L)	467	0.01	0.12	-0.5	0.6
Distribution & transportation (NACE G-I)	467	0.09	0.40	-1.6	2.0
Public sector (NACE O-Q)	467	0.10	0.49	-1.7	2.8

Table A37. Pairwise correlations by EU membership

old MS	INDUSTRY				SERVICES				
Education / Sector	**A**	**B-E**	**C**	**F**	**J**	**G-I**	**M-N**	**O-Q**	**R-U**
ISCED 0-2	**0.07**	**0.10**	**0.11**	**0.27*** **	**-0.05**	**-0.08**	**0**	**-0.30*** **	**-0.19*** **
ISCED 3-4	**-0.05**	**-0.19*** **	**-0.17** **	**0**	**-0.03**	**-0.01**	**0.11* **	**0.06**	**0.10**
ISCED 5-8	**0.04**	**0.01**	**0**	**-0.29*** **	**0.04**	**0.03**	**-0.11* **	**0.32*** **	**0.11* **

new MS	INDUSTRY				SERVICES				
Education / Sector	**A**	**B-E**	**C**	**F**	**J**	**G-I**	**M-N**	**O-Q**	**R-U**
ISCED 0-2	**0.06**	**0.13**	**0.15* **	**0.13**	**-0.01**	**0.08**	**-0.29*** **	**-0.21** **	**-0.28*** **
ISCED 3-4	**0.02**	**-0.03**	**0.02**	**0.01**	**-0.11**	**0.03**	**0.01**	**-0.07**	**0.03**
ISCED 5-8	**0.04**	**-0.11**	**-0.18** **	**-0.29*** **	**0.17** **	**-0.13**	**0.16** **	**0.44*** **	**0.07**

Note: Pairwise correlations derived using changes in employment shares over a 3 year time interval for old MS and new MS (countries that joined the EU after 2004). As a robustness check, we replicated the analysis using 5-years changes in employment shares but results were similar. The ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A38. One-way LSDV estimates

Model regressors / Dependant variable:	Δ employment share NACE (B-E)	Δ employment share NACE F	Δ employment share NACE J+(M-N)	Δ employment share NACE (G-I)	Δ employment share NACE (O-Q)
Δ employment share, education ISCED 5-8 (1 year lag)	-0.017	-0.052**	0.007	0.007	0.041**
	(0.011)	(0.022)	(0.009)	0.013	(0.020)
Δ employment share, education ISCED 3-4 (1 year lag)	-0.003	-0.028*	-0.003**	0.004	-0.001
	(0.002)	(0.017)	(0.001)	0.003	(0.004)
Δ employment share, age group 15-24 (1 year lag)	-0.070	0.111	-0.069**	-0.066	-0.039
	(0.057)	(0.091)	(0.033)	0.050	(0.059)
Δ employment share, age group 25-49 (1 year lag)	-0.057	-0.006	-0.012	0.007	0.009
	(0.036)	(0.040)	(0.026)	0.036	(0.044)
Constant	-0.312***	0.121	0.239***	0.047	-0.105
	(0.086)	(0.138)	(0.075)	0.073	(0.070)
Δ log real expenditure of general government (1 year lag)					0.012**
					(0.006)
Δ log real expenditure of general government (2 years lag)					0.011**
					(0.005)
Δ log labour productivity (2 years lag)				0.025**	
				(0.010)	
Δ log GERD per mil. inhabitants (1 year lag)			0.004**		
			(0.002)		
Δ log residential property index (1 year lag)		0.036***			
		(0.005)			
Δ log real effective exchange rate, based on ULC	-0.021*				
	(0.012)				
Observations	398	261	391	389	389
# of countries	28	28	28	28	28
R^2	0.23	0.47	0.13	0.06	0.32
Year dummies	Yes	Yes	Yes	Yes	Yes
Arellano-Bond AR(1) test, p-val.	0.08	0.01	0.06	0.38	0.01

Note: Robust standard errors are given in brackets. ***, ** and * denote statistical significance at 1%, 5% and 10% respectively.

Table A39. Two-way LSDV estimates

Model regressors / Dependant variable:	Δ employment share NACE (B-E)	Δ employment share NACE F	Δ employment share NACE J+(M-N)	Δ employment share NACE (O-Q)
Δ employment share, education ISCED 5-8 (1 year lag)	-0.011	-0.036	0.005	0.038**
	(0.012)	(0.026)	(0.009)	0.018
Δ employment share, education ISCED 3-4 (1 year lag)	-0.003	-0.021	-0.003*	0.001
	(0.002)	(0.018)	(0.002)	0.004
Δ employment share, age group 15-24 (1 year lag)	-0.089	0.060	-0.059*	-0.047
	(0.060)	(0.095)	(0.034)	0.062
Δ employment share, age group 25-49 (1 year lag)	-0.034	0.035	-0.007	-0.026
	(0.036)	(0.049)	(0.028)	0.050
Constant	-0.270**	0.142	0.268***	-0.127*
	(0.110)	(0.183)	(0.072)	0.073
Δ log real expenditure of general government (1 year lag)				0.010*
				(0.006)
Δ log real expenditure of general government (2 years lag)				0.008
				(0.006)
Δ log GERD per mil. inhabitants (1 year lag)			0.002	
			(0.002)	
Δ log residential property index (1 year lag)		0.031***		
		(0.005)		
Δ log real effective exchange rate, based on ULC	-0.022*			
	(0.013)			
Observations	398	261	391	389
# of countries	28	28	28	28
R^2	0.31	0.54	0.25	0.40
Year dummies	Yes	Yes	Yes	Yes
Country-specific time trends	Yes	Yes	Yes	Yes
Arellano-Bond AR(1) test, p-val.	0.69	0.03	0.98	0.49

Note: Robust standard errors are given in brackets. ***, ** and * denote statistical significance at 1%, 5% and 10% respectively.

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Abstract
Skills are at the core of improving individuals' employment outcomes and increasing countries productivity and growth while ensuring social cohesiveness. This is particularly relevant as today's global competition is characterized by a higher share of knowledge-based content which heavily relies on high-level cognitive and behavioral skills. The 1994-1998 International Adult Literacy Survey (IALS) and the 2012 Survey on Adult Skills (PIAAC) are unique datasets providing measures of individual cognitive skills for a representative sample of the adult age population across a number of OECD countries using methods of educational testing jointly with household survey techniques. Thus, they offer an exceptional opportunity to better understand how cognitive skills have evolved and how they are likely to influence our lives now and in the future, particularly in what refers to employment chances.

The aim of this technical report is threefold: (1) to analyse the current levels and distribution of skills in the working-age population of the sixteen Member States which participated in PIAAC; (2) to investigate to what extent these skills are important for labour market success; and (3) to examine how individuals (and the population) gain, lose and preserve their cognitive skills over time. To further complement this empirical evidence, we investigate the employment dynamics with respect to economic factors. The observed trends go in the direction of a concentration of employment in sectors which are more likely to require a higher educational level and consequently a higher level of skills. With all the caveats in mind, the reasoning behind this simple exercise is to grow awareness about the need to reinforce skills, and desirably, anticipate skills needs, through both efficient education policies and active labour market programs, including training.

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