



ISSN 2443-8030 (online)

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ECONOMIC BRIEF 054 | JULY 2020

EUROPEAN ECONOMY

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The cut-off date for the data in this paper was before the UK left the EU (therefore, the UK is still included in EU28 aggregate figures) and before the economic impact of the COVID-19 pandemic reached Europe.

Authorised for publication by Declan Costello, Deputy Director-General for Economic and Financial Affairs.

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Luxembourg: Publications Office of the European Union, 2020

PDF ISBN 978-92-79-77383-9 ISSN 2443-8030 doi:10.2765/846577 KC-BE-18-022-EN-N

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Facing the Digital Transformation: Are Digital Skills Enough?

By Maria Chiara Morandini, Anna Thum-Thysen and Anneleen Vandeplas

Abstract

Digitalisation presents great opportunities for economic growth and improvements in working conditions. At the same time, it brings challenges such as new skill requirements – with potentially important distributional implications in the absence of commensurate policy action. To facilitate the digital transition and reap its benefits, people will need a broad set of skills. The analysis in this paper suggests that both cognitive (numeracy, literacy and digital) and non-cognitive skills exhibit a strong and robust positive correlation with labour productivity. While cognitive skills remain very important, there are signs that non-cognitive skills are rapidly increasing in importance. In a world in which the task content of jobs is progressively de-routinised and changing faster than ever, adaptability, communication and collaboration skills, critical thinking, creativity, entrepreneurship, and readiness to learn become all the more important. The digital transformation calls for policies that foster strong foundation skills, promote life-long learning and strengthen the link between education, training and the world of work. Complementary structural policies that promote efficient resource allocation or that enhance investment in intangible assets can strengthen the link between skills and productivity. While education and training policies fall mostly under the responsibility of Member States, the EU can support human capital development by promoting cooperation and the exchange of best practices among Member States, and through targeted financial support.

Acknowledgements: We gratefully acknowledge helpful comments and suggestions from Erik Canton, Stephanie Carretero Gomez, Jorge Duran Laguna, Alexandr Hobza, Joanna Napierala, Karl Pichelmann as well as the participants of an inter-DG seminar on the role of skills in the digital transformation held in March 2019, an internal seminar at the World Bank in June 2019 and a ROA workshop at the University of Maastricht in November 2019.

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Introduction

The digital transformation presents great opportunities for economies around the world, including in the EU. It provides scope for productivity and economic growth, as well as for the improvement of working conditions such as health and safety conditions and wages. At the same time, like any other transition, digitalisation also brings challenges which need to be addressed in order to reap its full benefits. A particular challenge is the adaptation of the labour force to new skill requirements of the digital economy. The wider use of technology will no doubt lead to a higher demand for digital and technology-related skills. At the same time, there is growing acknowledgement of the increasing importance of non-cognitive¹ skills, such as communication and collaboration skills, creativity and critical thinking. Moreover, with economies and labour markets being in continuous flux, the capacity to learn and adapt to new tasks and jobs is becoming ever more important. Similar skills-related concerns have risen in view of ensuring a smooth and inclusive transition towards a climate-neutral economy.

The challenges we face

Digital technologies such as computers, the internet, digital platforms, robots, machine learning and other forms of artificial intelligence, and big data technologies have led to a "digital transformation", a process that uses digital technologies to create new or modify existing processes, products and services to cater better to business or customer needs. This process generates opportunities and drives long-term value and productivity (van Ark, 2018)². It also poses important challenges for our economy, particularly for the labour market.

The phenomenon of digital transformation extends beyond the automation of manufacturing assembly lines. Beyond manual tasks, analytical tasks involving decision-making also offer scope for digitalisation. Examples include a transport clerk using software to optimise transport solutions or a car mechanic using analytical software to diagnose problems with a car (see e.g. European Commission 2016a). Certain routine-based tasks in accounting, paralegal services and medical diagnostics can also be automated as the capacity of artificial intelligence technologies to write business reports, prepare legal

briefs, and diagnose diseases is improving (Acemoglu and Restrepo, 2018b).

As machines are taking over human tasks, there has been widespread concern over possible mass displacement of workers by robots. In an influential paper that sparked a heated debate, Frey and Osborne (2017) estimated that around 47% of US jobs would be at risk of automation. Based on the same methods, Bowles (2014) found that the corresponding proportion for EU countries of jobs at risk of automation ranges from 47% in Sweden to over 60% in Romania. Methodological improvements by Arntz et al. (2016) adopting a task-based rather than an occupation-based approach, and follow-up work by Nedelkoska and Quintini (2018) have brought these estimates down to 9% for the US and in the range of 7 % (Finland) to 33% (Slovakia) in Europe.³ At the same time, the proportion of jobs "at risk of automation" should not be equated with expected job losses from automation. As Arntz et al. (2016) underline, automation may not occur because of various hurdles (including economic or legal ones), and workers may adapt to automation by taking up new tasks within their job.

New technologies are also likely to *generate new jobs*. A number of recent studies suggest that the job creation effects of new technologies dominate their displacement effects, resulting in net employment growth (see e.g. Autor and Salomons, 2018; Gregory et al., 2019; Graetz and Michaels, 2018).⁴ Notably, while machines have substituted labour and displaced certain jobs, they also raise productivity, reduce production costs and prices, with positive impacts on product and labour demand in the automated sector. The labour demand impact of the automation in a specific industry is likely to depend on the elasticity of demand for the goods it produces (Bessen, 2018). Positive demand effects are also likely to spill over to other, non-automated sectors. Their magnitude is likely to hinge upon the allocation of the gains from innovations. If for example the gains from innovations are mostly appropriated by high-skilled workers and/or capital owners with a lower marginal propensity to consume than those who are displaced from their jobs, the positive impact on demand for products and labour may not materialise or to a lesser extent (Acemoglu and Restrepo, 2018b). Policy intervention can make a difference here, including through appropriately designed labour market institutions and tax-benefit systems.

Recent employment figures in the EU seem encouraging: in spite of the digital transformation gaining speed, in 2018 total employment in the EU stood at an all-time high (at almost 220 million for age group 20-64). Furthermore, a recent employer survey suggests that most employers in the EU do not expect major changes in staff numbers as a result of automation (ManpowerGroup, 2019).⁵

At the same time, there is reason for concern regarding the distributional effects of the digital transformation. Technological change can lead to a disruptive shift of tasks from human labour to machines, transforming jobs and tasks drastically (see e.g. Balliester and Elsheikhi, 2018). If demand is shifting away from certain types of tasks, jobs, and/or workers, this may have important distributional implications. The two predominant views in the literature today argue that employment is shifting away from low-skilled jobs (according to the *skills-biased technological change* hypothesis, see e.g. Bound and Johnson 1992; Katz and Murphy 1992) and from tasks with a higher routine content, which are easier to automate (according to the *routine-biased technological change* hypothesis, see e.g. Autor et al., 2003; 2006; Goos et al., 2009).⁶

Both hypotheses warn against a potential rise in inequality between lower-skilled and high-skilled individuals, as empirical analysis finds a higher routine-intensity of lower-skilled jobs (e.g. Marcolin et al., 2016; Nedelkoska and Quintini, 2018; Pouliakas, 2018; Fernández-Macías and Hurley, 2017). Under both scenarios, technological change and digitalisation are reinforcing the importance of skills for good employment and earnings prospects (e.g. Acemoglu, 2002). These inequalities also risk reinforcing regional divergence, as research has found routine jobs to be more concentrated in already lagging regions (EIB, 2019).

In addition to these distributional implications, failing to adjust the level and type of skills supply to changing labour market demands may have harmful macroeconomic effects. Individuals who would like to work but do not have the skills required for available jobs put upward pressure on unemployment and inactivity rates. Not only are higher skilled individuals more likely to have and hold a job, they also tend to be more resilient and able to adapt to disruptive changes in the workplace (Bechichi et al., 2019). Second, individuals who have a job but face relevant skills gaps are likely to have lower productivity than their co-workers with

more appropriate skills sets (see e.g. Vandeplas and Thum-Thysen, 2019). Moreover, skills shortages may hamper investment in high-value added sectors, and slow down the diffusion and adoption of new technologies and as such have a dampening impact on productivity and economic growth (see e.g. Andrews et al., 2018). In a recent survey, almost 8 out of 10 enterprises in the EU, in particular the most dynamic ones, report that difficulties in finding workers with the right skills constitute a barrier to investment. More than 6 out of 10 even declare it to be a *major* barrier to investment (EIB, 2019).

Hence, adjusting the level and type of skills supply to changing labour market demands is crucial to overcome the challenges mentioned and to reap the benefits of digitalisation.

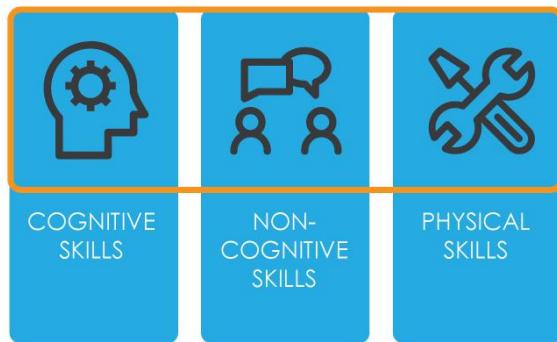
Which skills for the digital economy?

Science, technology, engineering and mathematics (STEM) skills, including ICT skills⁷, are considered essential in driving innovation, and delivering knowledge-driven growth and productivity gains (Shapiro et al., 2015; Peri et al., 2015; Deming and Noray, 2018).⁸ Demand for these skills has been growing since the early 2000s and growth is expected to continue – not only fuelled by the creation of new jobs requiring advanced technical skills, but also because of a strong anticipated replacement demand as a result of an ageing STEM workforce (Shapiro et al., 2015; EUSP, 2014a).⁹ Perceptions on STEM skills shortages are further exacerbated by the fact that technological progress is so fast that STEM skills quickly become obsolete and new STEM skills are always scarce (Deming and Noray 2018).

Eurostat estimates suggest that the share of ICT specialists (out of total employment) grew from 2.6% to 3.9% over the period 2005-2018. However, the demand for digital skills¹⁰ created by the digital transformation is much broader. Due to the increasingly widespread use of digital technologies, not only ICT-specialist but most jobs these days require some level of digital skills. Survey evidence suggests that in 2014, about 85% of jobs in the EU required at least a basic level of digital skills – and this number is expected to increase (Cedefop, 2018b).¹¹ Notably, 19% of adult employees reported needing basic digital skills (using internet or email), 52% needed moderate digital skills levels (using word processing and/or spreadsheet software) and

14% reported requiring advanced digital skills (for programming or statistical analysis) for their jobs. As such, digital skills increasingly enter the wider set of “foundation skills” (literacy, numeracy) considered essential for labour market participation.

Graph 1: Which skills for the digital economy?



Source: DG ECFIN.

However, the demand for skills created by the digital transformation goes beyond STEM (including ICT) skills. Employers increasingly report the need for a broader set of cognitive and non-cognitive skills to cope with the demands of the digital transition (Graph 1 and Box 1).¹² With increasing scope for automation of repetitive tasks, skills requirements are expected to shift gradually towards entrepreneurship, critical thinking and creativity and other skills used to carry out non-routine tasks in which workers hold a comparative advantage (Desjardins, 2018; Autor, 2015).

These include also people management skills, coordinating, collaborating and communicating with others, and emotional intelligence. Given the fast changes in job content expected to emanate from the digital transition, workers’ capacity to adapt, readiness to learn, and resilience are also key assets from their employers’ perspective. People with strong social skills provide leadership and help organising production processes in a more effective way. In fact, social skills and teamwork help to reduce coordination costs, allowing workers to specialise and work together more efficiently.

Recent literature indeed documents that workers with advanced technical skills are increasingly required to have well-developed “generic” or “transferable” skills of the nature listed above to promote innovation (Matturro et al. 2019; Toner, 2011; Gonzalez Vazquez et al., 2019), and that such skills are likely to command a rising premium in a digitalised economy (McKinsey Global Institute,

2017). Moreover, in view of the general decline of the manufacturing industry in Europe, innovation increasingly takes place in the service industry, where the non-STEM workforce plays an essential role in the innovation process.

Recent evidence from the US suggests that high-paying occupations increasingly require strong social skills (Deming, 2017; Deming and Kahn, 2018).¹³ OECD (2019) finds that workers that are more exposed to digital technologies at their workplace, perform more tasks involving management, communication, and selling. Anghel and Balart (2017) find a positive relation between individual earnings and non-cognitive skills that persists after controlling for foundation skills (*i.e.* PIAAC-based numeracy test scores). Kureková et al. (2016) highlight the importance of non-cognitive skills in low- and medium-skilled occupations based on an analysis of EURES-data for three European countries (Czech Republic, Denmark, Ireland).

At the same time, as the demand for cognitive and non-cognitive skills is growing, physical skills demand is fading (see for instance McKinsey, 2017). Robots and other machines are taking over tasks that require repetitive use of fine motor skills as well as those that require heavy lifting. This opens up new opportunities to integrate women and older workers, which are often considered to have less “muscle power” into traditionally (younger) male-dominated sectors such as transport.

Which skills do workers in the EU possess?

Compared to other regions of the world, there remains scope to improve the EU’s performance in terms of human capital for a digital economy and society. Notably, the EU scores below other advanced economies such as Norway, Korea, Iceland, Canada, China, US, Japan, Australia. At the same time, the top EU countries (Denmark, Netherlands, United Kingdom) are well ahead of the other advanced economies (Capgemini Consulting, 2016).

More than 40% of Europeans still lack “basic digital” skills, according to the Digital Economy and Society Index (DESI) (European Commission, 2019 and Graph 2).¹⁴ At the individual level, digital skills gaps act as a barrier to societal participation and exacerbate existing socio-economic inequalities. At the aggregate level, they can hinder further

expansion of e-commerce and e-government and the adoption of new technology in the business sector.

The share of enterprises with hard-to-fill vacancies for ICT specialists rose from 3% in 2012 to 5% in 2019 in EU28.¹⁵ These skills shortages disproportionately affect larger companies (250 employees or more): the share of large companies reporting such hard-to-fill vacancies rose from 18% in 2012 to 30% in 2019. Their incidence is (unsurprisingly) highest in the ICT sector (42%), and higher in professional services (9%) than in business support services (5%) and in the manufacturing sector (4%). Only 1% of companies with more than 10 employees report hard-to-fill vacancies for ICT specialists in the construction and in the accommodation and food service sectors.

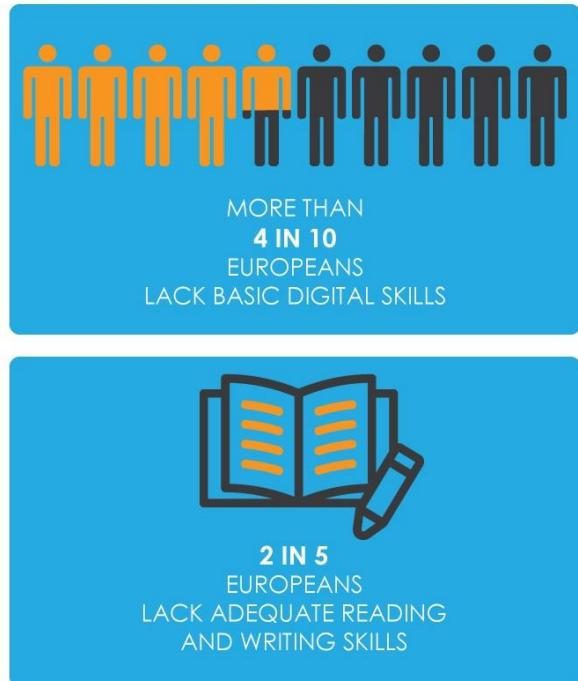
Similar observations can be made with regard to other skills types. Studies based on PIAAC data show that while some EU Member States are among the top of the global league in terms of average numeracy and literacy skills, others lag considerably behind. Within countries, there is even more variation in skills proficiency than between countries. Around 20% of the European population at working age lacks the level of numeracy and literacy skills that is considered essential for successful participation in the economy and in society overall (European Commission, 2013a and Graph 2). Less is known about how European adults perform in terms of non-cognitive skills.

The OECD's PIAAC dataset allows exploring the variation in different types of skills across 20 countries and a range of sectors in the EU. While the dataset also covers inactive and unemployed individuals, for the remainder of this paper we will focus on the skills of working individuals only, as we will then relate these skills to economic performance as measured by labour productivity.

We consider cognitive foundation skills (literacy, numeracy and problem solving), technical digital skills (simple and more complex ones), and a set of non-cognitive skills (self-organisation, interaction and communication; managing and supervision; readiness to learn and creativity; trust in persons; conscientiousness). Lastly, we also consider physical skills. Only the cognitive foundation skills are measured directly; the other skills are assessed based on the extent to which they are used on the job as a proxy. Our skills typology is strongly inspired by earlier work based on PIAAC by Grundke et al.

(2016) who present a normative taxonomy of skills that can be operationalised using data from the PIAAC survey (see Box 1).

Graph 2: Upskilling challenges Europe faces



Source: Digital Economy and Society Index (DESI) 2017 and PIAAC data 2013.

Graphs 3-5 provide a first intuition in the variation in skills levels (cognitive, non-cognitive, physical skills) across countries and (EU-level aggregated) sectors. The data suggest variation in workers' skills levels across countries. For cognitive skills, the Netherlands, Belgium (Flanders) and Estonia stand out as best performers; but Slovakia, Czechia, Finland, Hungary and Denmark perform well, too. At the other end, Greece, Cyprus, Spain and France perform rather weakly. There is no clear relationship emerging between cognitive skills and other types of skills at the country level. Also in statistical terms, there is no significant correlation. The best performers in terms of non-cognitive skills use are Denmark, Finland and Sweden, but also Poland, Ireland and Spain perform relatively well. On the other hand, Greece, Lithuania and Cyprus perform weakly at this level – making Greece and Cyprus bottom performers both in cognitive and non-cognitive skills among the EU countries covered by PIAAC. Physical skills are used most often in Slovenia and Lithuania, Ireland and Poland; and least often in Hungary, France, Finland and Belgium (Flanders).

Box 1: DEFINITION OF SKILLS VARIABLES

Our analysis focuses on employed individuals in age group 16-65 which report their sector of work. 21 EU countries are covered by PIAAC: AT, BE-FL, CY, CZ, DK, EE, FI, FR, DE, IE, IT, NL, PL, SK, ES, SE, UK (Round 1 in 2011-12), EL, LT, SI (Round 2 in 2014-15) and HU (Round 3 in 2017). Prior to the compilation of the indicators, raw data were subject to min-max normalisation ($y' = [y - \min(y)]/[max(y)-\min(y)]$). This standardisation rescales the data to vary between 0 and 1 which increases their suitability for inclusion in a composite indicator.

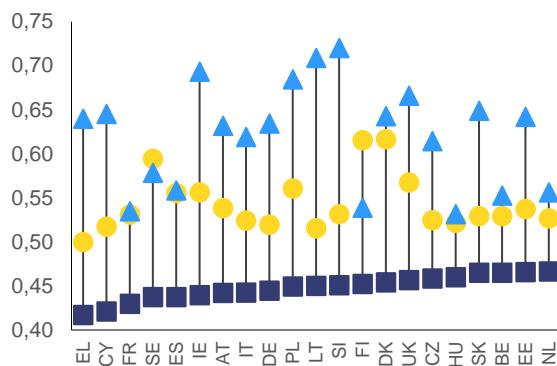
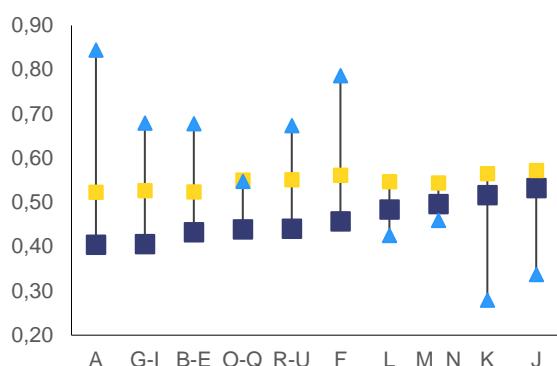
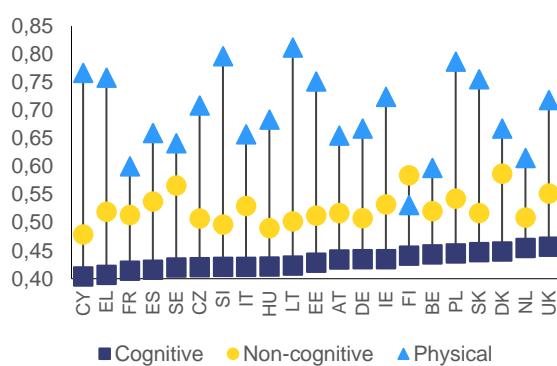
Cognitive skills:

- **Foundation skills:**
 - o *Literacy skills:* Test scores from direct literacy tests administered in PIAAC survey
 - o *Numeracy skills:* Test scores from direct numeracy tests administered in PIAAC survey
 - o *Problem-solving skills:* Test scores from direct tests on problem-solving in ICT-rich environments administered through the PIAAC survey. Not implemented and hence unavailable for CY, ES, FR, and IT.
- **Digital skills:**
 - o *Simple digital skills:* Indicator calculated as the simple average of replies to 3 background questions on tasks performed at work [frequency of email use; frequency of simple internet use; frequency of word use]
 - o *Complex digital skills (ICT skills):* Indicator calculated as the simple average of replies to 3 background questions on tasks performed at work [frequency of excel use; frequency of transactions through internet such as banking or selling/buying; frequency of programming language use]
- **Aggregate indicator:** Simple average of the cognitive skills indicators listed above, excluding problem-solving skills due to its unavailability for several countries.

Non-cognitive skills:

- *Self-organisation skills:* Simple average of replies to 6 background questions on tasks performed at work [extent of own planning of the task sequences; extent of own planning of style of work; extent of own planning of speed of work; extent of own planning of working hours (duration of work); frequency of planning own activities in the job; frequency of planning the use of own time]
- *Interaction and communication skills:* Simple average of replies to 6 background questions on tasks performed at work [time collaborating or cooperating with co-workers; frequency of information sharing with co-workers; frequency of giving speeches and presentations; frequency of client interaction selling a product or a service; frequency of negotiations within the firm or with other outside actors; frequency of communication through internet]
- *Managing and supervision skills:* Simple average of replies to 5 background questions on tasks performed at work [frequency of supervising people; frequency of planning activities of others; frequency of instructing and teaching people; frequency of advising people; frequency of persuading or influencing others]
- *Readiness to learn and creativity:* Simple average of replies to 5 background questions on personality traits [If I don't understand something, I look for additional information to make it clearer; When I come across something new, I try to relate it to what I already know; When I hear or read about new ideas, I try to relate them to real life situations to which they might apply; I like learning new things; I like to figure out how different ideas fit together]
- *Trust in persons:* Simple average of replies to 2 background questions on personality traits [trust only in few people; fear of being exploited by others]
- *Conscientiousness:* Reply to background question on personality trait [I like to get to the bottom of difficult things]
- *Aggregate indicator:* Simple average of the 6 non-cognitive skills indicators listed above

Physical skills: Indicator calculated as the simple average of replies to 2 background questions on tasks performed at work [Frequency of working physically over long periods; Frequency of working accurately with fingers]

Graph 3: Cross-country variation in skills levels**Graph 4: Cross-sector variation in skills levels****Graph 5: Variation in skills industry sector (B-E)**

Note: Average skills levels for working individuals aged 16-65. Skills are measured on a scale from 0-1. Levels are not comparable across skills types. 'Cognitive': Aggregate cognitive skills indicator; 'Non-cognitive': Aggregate non-cognitive skills indicator; 'Physical': Physical skills indicator (see Box 1 for details). Sectoral classification: A: Agriculture; B-E: Industry (without construction); F: Construction; G-I: Wholesale & retail, food & accommodation; J: Information & communication; K: Finance and Insurance; L: Real estate; M_N: Professional, scientific and technical, administrative and support service activities; O-Q: Public administration, defence, education, human health & social work; R-U: Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organisations and bodies.

Source: Authors' own calculations based on PIAAC.

The cross-sector comparison of EU-level average skills levels (Graph 4 suggests that workers in the Information and Communication sector (J) and in the Financial and Insurance sector (K) have the highest average level of cognitive skills, and the lowest level of physical skills use. Interestingly, these sectors also show the highest levels of non-cognitive skills. Next feature the business and professional services and real estate sectors (M-N and L). Physical skills are used most intensely in the agricultural (A) and the construction (F) sector. Cognitive skills are lowest in the agricultural (A) and in the lower-value services (trade, transport, food & accommodation: G-I) sectors. The manufacturing sector comes next, with slightly higher cognitive and physical, but lower non-cognitive skills than the lower-value services sectors. Graph 4 suggests a somewhat stronger pattern of correlation between different skills types: even if the correlation is not perfect, higher cognitive skills seem to coincide broadly with higher non-cognitive skills and lower physical skills use.

The data however also show strong within-sector variation. To illustrate this, Graph 5 presents the variation in average skills levels for the industry sector (B-E). The data suggest for instance that the industry sector is substantially more knowledge-intensive in the Netherlands, Denmark and Slovakia than in Cyprus, Greece and France. Physical skills are more important in the industry sectors in Lithuania, Slovenia and Poland than for example in Finland, Belgium or France. These differences not only reflect industrial specialisation patterns, but also the way production processes are organised. Graph 5 also shows the positive (and significant) cross-country correlation between cognitive and non-cognitive skills, once the data are purged from sectoral influences.

The skills-productivity nexus

The positive correlation between labour productivity and various cognitive measures has received ample attention in the existing literature (see e.g. Delong et al., 2003; Bishop, 1989; Hanushek and Woessmann, 2010a; 2010b; 2020).

Less attention has gone out to the correlation between non-cognitive or non-cognitive skills and productivity. Recently, some studies have suggested that higher paying jobs increasingly require social skills (see Deming (2017) for a brief review). If we take on the usual assumption that wage differentials

at least partially reflect productivity differentials, a positive wage premium on non-cognitive skills implies that non-cognitive skills imply a productivity advantage. Woolley et al. (2010) finds that social sensitivity in a group context predicts productivity, even after controlling for average (or maximum) intelligence of individual group members.

In what follows, we use OECD's PIAAC data to explore the nexus between productivity and different types of skills.¹⁶ To this extent, we calculate country-sector average skills levels of the different types listed in Box 1. As we only have a single round of observations on skills in PIAAC, we are limited to using cross-sectional analysis. We explore the within-country sectoral variation in average skills levels of workers to investigate the relationship between skills and labour productivity.¹⁷ Sector averages are weighted using the individual weights provided by the PIAAC dataset to improve sample representativeness. Labour productivity data draw on annual national accounts as reported by Eurostat for 2013, and measured as sectoral gross value added in PPS/hour worked.¹⁸

The underlying hypothesis of our analysis is that workers (broadly) sort into different sectors according to their skills endowments, and that these

skills endowments may have an impact on sectoral productivity. There is a clear monetary incentive to do so, as higher productivity sectors generally pay higher wages. It is consistent with general theories on structural change, which predict that, over time, labour and other resources broadly reallocate to sectors with higher productivity, contributing to economic growth. It is also consistent with literature showing that human capital and skills facilitate adaptation to economic change (Hanushek et al., 2017).

The regressions use a simple OLS reduced form framework with $\log(\text{labour productivity})$ as dependent variable ($\log(y_{i,j})$), skills indicators as explanatory variable ($s_{i,j}$), and country fixed effects (d_i) to control for factors that have a country-wide impact on productivity levels. Hence, we estimate the following equation:

$$\log(y_{i,j}) = \alpha + \beta s_{i,j} + d_i + \varepsilon_{i,j}$$

for country i and sector j .

The descriptive statistics of the variables used in the regressions are presented in Table 1. The regression results are displayed in Table 2 and Table A1.

Table 1: Descriptive statistics

	Nr. Obs.	Mean	SD	Min	Max
Cognitive skills					
Literacy skills	189	0.596	0.043	0.480	0.699
Numeracy skills	189	0.592	0.040	0.487	0.678
Problem-solving skills	153	0.529	0.041	0.414	0.619
Simple ICT skills	189	0.737	0.120	0.418	0.950
Complex ICT skills	189	0.333	0.087	0.151	0.522
<i>Aggregate cognitive skills indicator</i>	189	0.461	0.047	0.355	0.556
Non-cognitive skills					
Self-organization	189	0.644	0.087	0.423	0.829
Interaction and communication	189	0.450	0.052	0.303	0.576
Managing and supervision	189	0.365	0.089	0.136	0.556
Readiness to learn and creativity	189	0.688	0.050	0.517	0.811
Trust in persons	189	0.314	0.096	0.105	0.616
Conscientiousness	189	0.661	0.075	0.448	0.800
<i>Aggregate non-cognitive skills indicator</i>	189	0.548	0.040	0.400	0.672
Physical skills	189	0.591	0.188	0.067	0.939
Log(labour productivity)	189	3.348	0.562	1.670	4.873

Table 2: Regression results for the relationship between labour productivity and different skill types (% changes)

VARIABLES	(1) logLP	(2) logLP	(3) logLP	(4) logLP	(5) logLP	(6) logLP	(7) logLP	(8) logLP	(9) logLP	(10) logLP	(11) logLP	(12) logLP	(13) logLP	(14) logLP
<i>Cognitive skills</i>														
Literacy skills	10.057*** (0.765)													
Numeracy skills		11.347*** (0.772)												
Problem-solving skills			10.181*** (0.892)											
Simple digital skills				2.522*** (0.269)										
Complex digital skills					3.726*** (0.358)									
Aggregate cognitive skills						7.474*** (0.631)								
<i>Non-cognitive skills</i>														
Self-organisation						0.927 (0.620)								
Interaction and communication							5.472*** (0.713)							
Managing and supervision								4.248*** (0.415)						
Readiness to learn and creativity									6.837*** (0.753)					
Trust in persons										6.171*** (0.799)				
Conscientiousness											6.494*** (0.720)			
Aggregate non-cognitive skills												6.898*** (1.305)		
<i>Physical skills</i>														
Physical skills														-1.985*** (0.149)
Constant	-2.543*** (0.474)	-3.356*** (0.480)	-2.072*** (0.502)	1.649*** (0.241)	2.319*** (0.176)	0.067 (0.316)	2.828*** (0.471)	1.198*** (0.333)	1.909*** (0.206)	-1.169** (0.532)	1.592*** (0.287)	-0.767 (0.492)	-0.238 (0.722)	4.660*** (0.151)
Observations	189	189	153	189	189	189	189	189	189	189	189	189	189	189
Country-level fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared (adjusted)	0.571	0.619	0.567	0.428	0.470	0.525	0.138	0.355	0.463	0.416	0.357	0.413	0.252	0.576

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: own calculations based on OECD PIAAC 1st cycle data (2010 - 2017), employed individuals and weighted according to PIAAC's sample weights and National Accounts sectoral data for sectors classified at NACE-2 letter level (A-U) (2013) Notes: (1) The reported coefficients are based on linear regressions at sectoral level including dummy variables at country level. They do not represent individuals' returns to skills. (2) Skills are measured on a 0-1 scale and labour productivity (defined as gross value added expressed in purchasing power parity in over total hours worked) is measured on a logarithmic scale. Coefficients can hence be interpreted as a %-change in labour productivity associated with a 0.01-unit (1%) change in the respective type of skill.

The results suggest an extremely strong link between skills and labour productivity. An increase by 1% in literacy test scores (assessed on a 0-1 scale) is associated with a 10% increase in labour productivity, and this relationship is statistically significant at the 1% level. Correlations with numeracy and problem-solving test scores are of the same magnitude, and even slightly stronger.¹⁹ For instance, a 1% increase in numeracy test scores is associated with a 11.3% increase in labour productivity. This is in line with earlier PIAAC-based studies finding a stronger link between wages and numeracy skills than with literacy skills (Hanushek et al., 2015). It is important to note that these are correlations, which do not necessarily imply direct causality.²⁰ Indeed, there are some factors (such as e.g. capital) that could contribute to explaining why labour productivity is higher in skills-intensive sectors. At the same time, we decided not to control for capital intensity in the regressions, as we believe increasing capital is one of the channels through which skills intensity can impact productivity (cfr. the rich literature on capital-skills complementarity initiated by Griliches, 1969).

The links with task-based ICT skills indicators are strong as well, albeit a bit less than with the test score indicators: a 1% increase in simple ICT skills is associated with a 2.5% increase in labour productivity, a 1% increase in complex ICT skills with a 3.7% increase in labour productivity. The relationship between labour productivity and the aggregate cognitive skills indicator is (unsurprisingly) somewhere in between: a 1% increase on the aggregate cognitive skills indicator translates into a 7.5% increase in labour productivity. It is important to note, meanwhile, that these are reduced-form regressions, and it may be argued that there are unobserved variables that are positively correlated with both skills and labour productivity, such as e.g. fixed capital. However, we chose not to control for fixed capital, as we believe that human capital is a determinant of fixed capital formation, and controlling for fixed capital would filter out one of the potential channels through which human capital can influence labour productivity.

For most of the cognitive skills indicators (except for simple ICT skills), the coefficients remain statistically significant even after introducing sector fixed effects in addition to the country fixed effects. The relatively smaller size of the coefficients on digital skills should be seen in light of the different measurement methodology (these are task-based

indicators rather than direct skills test scores, which might imply some measurement error), but also, more importantly, these indicators show stronger variation (larger standard deviations) than the test score indicators (Table 1).

The relationship between labour productivity and non-cognitive skills is also relatively strong, even if a bit weaker than the one with cognitive skills.²¹ While the relationship with the variable *self-organisation* is not statistically significant, for all other non-cognitive items considered, a 1% increase in the item is associated with a 4-7% increase in labour productivity (see Table 2). A 1% increase in the aggregate non-cognitive skills indicator is associated with a 6.9% increase in labour productivity. The non-significance of the coefficient on *self-organisation* is mostly driven by the agricultural sector (A), which combines low labour productivity with high rates of self-employment and self-organisation. If the agricultural sector is dropped from the analysis, the coefficient on self-organisation becomes positive and statistically significant at the 1% level.²²

For most of the non-cognitive skills items (except for self-organisation), the coefficients remain positively statistically significant also after introducing an indicator for aggregate cognitive skills. When already accounting for cognitive skills, a 1% increase in the non-cognitive item is associated with a 1-2% increase in labour productivity (see Table A1). Aggregate non-cognitive skills do not have additional explanatory power on top of aggregate cognitive skills for labour productivity, which is due to the special nature of the relationship between self-organisation and labour productivity. When excluding this item from the aggregate non-cognitive skills indicator, its coefficient becomes positive (indicating a 5% increase in productivity) and statistically significant at the 1% level.

The physical skills indicator, on the other hand, shows a strongly negative relationship with labour productivity, with a 1% increase in this indicator translating into a 2% reduction in labour productivity, suggesting that sectors that use physical skills more intensely generally have lower labour productivity. This finding is robust to excluding the agricultural sector.

In sum, our analysis of PIAAC data confirms that both cognitive and non-cognitive skills are associated with higher labour productivity. At the same time, we found a negative relation between labour productivity and physical skills use. On the contrary, we found a negative relation with physical

work. As industries requiring physical skills use are more likely to have lower productivity and pay lower wages, employment can be expected to shift increasingly towards higher productivity sectors, which require higher levels of cognitive and non-cognitive skills.

The strengthening demand for non-cognitive skills in the context of the digital transformation may facilitate the labour market integration of women and older workers, who are often considered to have stronger social skills (see e.g. Kelan, 2008; Kafetsios, 2004). Our data indeed suggest a positive and statistically significant impact of age on the majority of the considered non-cognitive skills measures (with the exception of *Interaction and Communication* and *Readiness to learn and Creativity*). At the same time, they suggest a negative impact of age on cognitive skills, in line with the existing academic literature. Women score particularly good in terms of *Readiness to learn and creativity*, *Trust in persons*, and *Conscientiousness*. Interestingly, these are the ones that are not measured through tasks performed at work and therefore be less plagued by measurement error. In this context, work by Van der Velden and Bijlsma (2019) is particularly worth mentioning, as it highlights the difference between skills endowments and the actual use of these skills at work.

In spite of the growing importance of non-cognitive skills in the workplace, however, these skills still tend to be overlooked in formal education curricula in many countries (Gonzalez Vazquez et al., 2019; García, 2014). While non-school factors such as family background play an important role, there are some signs that certain interventions can effectively foster non-cognitive skills through education and training (Heckman and Kautz, 2012; Kautz et al., 2017; Chernyshenko et al., 2018). Targeted interventions and the use of specific learning practices while teaching cognitive skills at pre-school and school age seem the most effective strategies, but programs at later age can also play an important role. There is some evidence that mobility programs such as Erasmus play a role in strengthening social, entrepreneurship and leadership skills (European Commission, 2014). However, in all, research in this area remains in its infancy.

While our analysis has not explicitly focused on entrepreneurship skills, several of the considered non-cognitive skills are key for entrepreneurs. In spite of the paucity of comparable data, on average, people in the EU are considered to have relatively

weak entrepreneurship skills compared to other economies such as the United States, Brazil and China – owing to education systems, but also broader policy settings (such as the regulatory environment for businesses and the design of tax systems) (EUSP, 2014b; European Commission, 2013b; Wilson, 2008). Efforts have been undertaken (including at the EU level) to integrate entrepreneurship education more strongly into education and training curricula, but more remains to be done.

Policy conclusions

The analysis in this paper suggests that cognitive as well as non-cognitive skills exhibit a strong and robust positive correlation with aggregate labour productivity. To facilitate profound economic transitions, people will need a broad set of skills. While cognitive skills remain very important, there are signs that non-cognitive skills are also rapidly increasing in importance. In a world in which the task content of jobs is progressively de-routinised and changing increasingly fast, adaptability, communication and collaboration skills, problem-solving, critical thinking, creativity, entrepreneurship, and readiness to learn become all the more important. At the individual level, the existing literature extensively documents how stronger skills provide workers with better opportunities for jobs and higher earnings, which is the best prevention against poverty and social exclusion. Cognitive skills have also been found to be positively related to health, trust, political efficacy, and active citizenship (OECD, 2019b).

With the digital and environmental transitions in sight, and demographic change calling for strengthened efforts to raise labour productivity, skills are expected to further increase in importance as drivers of individual well-being and macroeconomic performance. People's competences are key to successfully manage transitions spurred by technological change, climate change, globalisation, migration and ageing and to counteract rising inequalities. Skills are crucial not only to foster urgently needed innovations, but also to enable the adoption and diffusion and continuous further development of new knowledge and technologies. As such, human capital underpins EU's competitiveness in a global, increasingly digital and knowledge-based economy.

Societies with a well-qualified labour force are more resilient to shocks, and human capital is also essential for economic and social convergence. High

quality education and training systems are key to develop these skills – with investments as from an early age onwards providing the necessary foundations for lifelong learning. Given the increasing importance of non-cognitive skills in the workplace (and beyond), more attention is needed to develop these skills in education and training curricula at all levels.

Effective education and training policies first and foremost require sufficient financial resources. Investing in people's education and training is one of the best investments a society can make. Spending on education and training should be adequate, efficient and sustainable. While public money accounts for the bulk of spending on education and training in Europe, experiences across Member States show that there are successful ways to also attract co-financing from the private sector or individuals, without reducing access to training.

These resources must then be used to provide high-quality and inclusive education and training – to ensure that no one leaves initial education without the basic level of foundational skills that is necessary to thrive in our economy and society. To ensure that workers can acquire the skills demanded by the evolving needs of the labour market, accessible and widely available high-quality opportunities to upskill and reskill are key – and should be accompanied by public and private support to reach out to those who need training most but are less likely to pro-actively seek it, such as low-skilled and older workers.

Lower levels of skills mismatch in the labour market are associated with better economic performance (Vandeplas and Thum-Thysen, 2019). Mismatches can be reduced by providing all individuals with strong foundational skills, which enable and empower them to upskill and reskill in response to evolving labour market opportunities. To make education and training systems more labour market relevant, links with the world of work can be strengthened. Successful strategies include the expansion of work-based learning schemes, better career guidance (drawing on graduate tracking surveys and reports on expected skills needs by growing sectors), the involvement of social partners in the development and update of education and

training curricula, and the use of effective tools for workforce planning in specific sectors (such as healthcare and education).

Highly skilled workers are most productive if they are matched with jobs that fully utilise their skills. Generating these high-skilled occupations requires complementary investments in fixed assets (such as machinery and equipment) as well as in intangible assets (such as research, data and software). The link between skills and productivity can also be strengthened by structural policies that are favourable to the creation of skilled jobs, such as a business environment that promotes investment, and regulations that foster efficient resource allocation.

Moreover, if the ongoing economic transitions are strengthening demand for skills, they risk exacerbating existing inequalities between highly skilled and less skilled workers. To mitigate this, policy measures are required to mitigate pre-market, in-market and post-market drivers of inequality. Addressing pre-market drivers implies providing equal opportunities to all individuals, e.g. equal access to infrastructure, education, health care. Policies targeting in-market drivers of inequalities aim supporting sustainable and equitable growth e.g. through product and labour market regulations and competition policies that preserve the level playing field and reduce entry barriers for smaller firms and more vulnerable workers. Finally, policies in the post-market stage can alleviate market income inequalities through redistributive tax and benefit systems.

Inclusive labour markets should draw on the skills and talents of all, including the low-skilled and other vulnerable groups. In the global race for talent, we need to nurture our skilled workers, reduce brain drain, while facilitating mobility of EU citizens, attracting talent from abroad and making better use of migrants' skills.

While education and training policies fall mostly under the responsibility of Member States, European cooperation in the area of education and training policy allows Member States to exchange best practices and learn from each other. Other EU-level policies also support the development of Europe's human capital base (see Box 2).

Box 2: EU-LEVEL ACTION IN THE AREA OF EDUCATION AND SKILLS

- European policy cooperation in the area of education is governed by *ET 2020*, the strategic framework for European cooperation in education and training. It provides a forum that allows Member States to exchange best practices and learn from each other and is implemented through working groups, peer learning activities, peer reviews, peer counselling, annual reporting on a set of benchmarks through the Education and Training monitor, analytical contributions to the *European Semester* and so on.
- Over recent years, different actions were undertaken to build a *European Education Area*, with two major packages of initiatives launched in 2018 – including inter alia a *Digital Education Action Plan* (COM(2018)22), and *Council Recommendations on Key Competences for Lifelong Learning* (2018/C 189/01), *on High Quality Early Childhood Education and Care Systems* (2019/C 189/02), and *on a comprehensive approach to the teaching and learning of languages* (2019/C 189/03). The Recommendation on Key Competences considers not only cognitive but also non-cognitive skills.
- The *New Skills Agenda for Europe* (COM/2016/0381 final) was adopted by the Commission in 2016, and launched 10 actions to make the right training, skills and support available to people in the EU, mainly aimed at improving the quality and relevance of training; making skills more visible and comparable, and improving information and understanding of skills demand patterns to enable people to make better career choices, find quality jobs and improve their life chances. The actions include inter alia a *Council Recommendation on Upskilling Pathways* (2016/C 484/01), sectoral initiatives to identify skills needs and appropriate responses, the launch of a *Digital Skills and Jobs Coalition*, and support to develop graduate tracking systems at the Member State level.
- In 2017, the European Pillar of Social Rights was jointly proclaimed by Council of the European Union, the European Parliament and the Commission. It puts forward 20 principles and rights, to serve as a compass for renewed socio-economic convergence in Europe. The first principle says that “*everyone has the right to quality and inclusive education, training and life-long learning in order to maintain and acquire skills that enable them to participate fully in society and manage successfully transitions in the labour market*”.
- In her Political Guidelines, Von der Leyen announced new initiatives in the area of education and skills, notably to make the *European Education Area a reality by 2025*, updating the *Digital Education Action Plan*, and the *Skills Agenda*. Discussions have also started over a post-2020 framework for European cooperation in education and training.
- The *European Semester*, the annual cycle of economic policy coordination of the Commission, identifies structural challenges in education and training systems (and complementary policy areas) at the Member State level and provides Country Specific Recommendations to address these.
- The European Commission also supports education and skills in its Member States through funding from the European Social Fund+, the European Regional Development Fund, InvestEU, Erasmus+, Horizon Europe, Digital Europe, and the Reform Support Programme, as foreseen in its proposal for a new Multiannual Financial Framework (2021-27).

Annex

Table A1: Regression results for the relationship between labour productivity and different skill types (% changes)

VARIABLES	(1) logLP	(2) logLP	(3) logLP	(4) logLP	(5) logLP	(6) logLP	(7) logLP	(8) logLP	(9) logLP	(10) logLP	(11) logLP	(12) logLP	(13) logLP	(14) logLP
Aggregate cognitive skills		10.280*** (0.690)		6.280*** (0.747)		5.245*** (0.731)		6.057*** (0.913)		6.517*** (0.818)		6.060*** (0.903)		8.363*** (0.838)
Self-organisation	0.927 (0.620)	-3.477*** (0.503)												
Interaction and communication			5.472*** (0.713)	2.061*** (0.723)										
Managing and supervision					4.248*** (0.415)	2.324*** (0.452)								
Readiness to learn and creativity							6.837*** (0.753)	2.088** (0.982)						
Trust in persons									6.171*** (0.799)	1.621* (0.889)				
Conscientiousness											6.494*** (0.720)	2.007** (0.926)		
Aggregate non-cognitive skills													6.898*** (1.305)	-2.213 (1.380)
Constant	2.828*** (0.471)	1.238*** (0.327)	1.198*** (0.333)	-0.248 (0.329)	1.909*** (0.206)	0.225 (0.296)	-1.169** (0.532)	-0.706 (0.480)	1.592*** (0.287)	0.008 (0.316)	-0.767 (0.492)	-0.600 (0.439)	-0.238 (0.722)	0.854 (0.583)
Observations	189	189	189	189	189	189	189	189	189	189	189	189	189	189
Country-level fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared (adjusted)	0.138	0.629	0.355	0.545	0.463	0.588	0.416	0.535	0.357	0.532	0.413	0.536	0.252	0.530

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: own calculations based on OECD PIAAC 1st cycle data (2010 - 2017), employed individuals and weighted according to PIAAC's sample weights and National Accounts sectoral data for sectors classified at NACE-2 letter level (A-U) (2013) Notes: (1) The reported coefficients are based on linear regressions at sectoral level including dummy variables at country level. They do not represent individuals' returns to skills. (2) Skills are measured on a 0-1 scale and labour productivity (defined as gross value added expressed in purchasing power parity in over total hours worked) is measured on a logarithmic scale. Coefficients can hence be interpreted as a %-change in labour productivity associated with a 0.01-unit (1%) change in the respective type of skill.

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¹ In the literature across different disciplines and in the public debate, a wide set of terms is used: e.g. soft skills, non-cognitive skills, socio-emotional skills, etc. Addressing this conceptual and terminological debate is beyond the scope of this note. Here we refer simply to non-cognitive skills. For a brief overview of the taxonomy and measurement issues see for instance Gonzalez Vazquez et al., 2019 (in particular chapter 2, box 5, p. 31). For an example of research, which aims at clarifying the debate, see for instance Rowan-Kenyon et al. (2017).

² See Bart van Ark's intervention at the ECFIN's Annual Research Conference 2018: "The productivity challenge: jobs and incomes in the dawning era of intelligent robots", 19th November 2018. Available at: https://ec.europa.eu/info/sites/info/files/economy-finance/van_ark.pdf.

³ Note however that the estimates rely on PIAAC (2012) data and therefore do not cover all EU countries. BG, HR, LV, LU, HU, MT, PT and RO are not included in the study.

⁴ Acemoglu and Restrepo (2018a) propose three channels through which technological change raises labour demand: the productivity channel, the capital accumulation channel, and the deepening of automation channel.

⁵ In particular, the survey results suggests that employers are expecting to keep staff headcounts at par in BG, PT, IE, UK, AT, SI, FR, PL, DE, EL, SE, FI, and HR, while they are expecting automation to lead to a staff reduction in BG, HU, CZ, SK and RO and to a staff increase in NL, ES, and IT (for more details, see ManpowerGroup (2019)).

⁶ "Routine tasks" are limited well-defined set of activities that can be accomplished by following explicit rules (Autor et al. 2003) and are more easily executed by machine, as technology advances.

⁷ ICT skills target to professionals working in the ICT sector.

⁸ Some have argued that there is significant heterogeneity within the STEM field, with engineers and ICT graduates fetching a substantially higher wage premium than e.g. graduates in biology, chemistry, physics and mathematics (Deming and Noray, 2018).

⁹ At the same time, the STEM labour market is very heterogeneous, and labour market conditions may vary across specializations (Xue and Larson, 2015).

¹⁰ Digital skills label the competence needed by the population to use digital technologies (see for example the DESI Human Capital Dimension which is calculated as the weighted average of the two sub-dimensions: 2a Internet User Skills (50%) and 2b Advanced Skills and Development (50%); <https://digital-agenda-data.eu/datasets/desi/indicators#desi-dimensions>). The notion of "ICT skills" refers more to professionals.

¹¹ The data are based on the Cedefop European skills and jobs survey (ESJS), which is designed as to be representative of adults aged 24-65 in 28 EU Member States. A 2015 survey by Eurofound (the 6th European Working Conditions Survey) finds a slightly lower estimate: around 56% of surveyed employees reported working with computers, laptops, smartphones etc., ranging from 41% in PT to 78% in DK.

¹² See for instance Andrews et al. 2018; Anghel and Balart 2017; Annunziata and Bourgeois 2018; Bart Van Ark, 2018. Frey and Osborne 2017; Grundke et al. 2017; Marcolin et al. 2016; Oldensi 2014, 2012; Toner 2011; World Economic Forum 2016 but also Luksha et al. 2015; WEF 2016, McKinsey 2017, Pouliakas 2018, LinkedIn 2019 or ManpowerGroup 2019.

¹³ This is by no means a new phenomenon: Weinberger (2014) already noted the increasing complementarity between cognitive and social skills in the US labour market.

¹⁴ The Digital Economy and Society Index (DESI) is a composite index that summarises relevant indicators (connectivity, human capital/digital skills, use of Internet services by citizens, integration of digital technologies by businesses, digital public services) on Europe's digital performance and tracks the evolution of EU member states in digital competitiveness.. See: <https://ec.europa.eu/digital-single-market/en/desi>

¹⁵ See Eurostat variable isoc_ske_itrcrn2. Part of the increase could be related to the economic recovery.

¹⁶ In reality, cognitive and non-cognitive skills are of course difficult to isolate from each other. Personality traits influence the development of cognitive ability and its evolution over a lifetime (Borghans et al., 2008; Heckman and Kautz, 2012). However, for the purpose of our analysis we consider these skills as separable.

¹⁷ The real estate sector (L) is dropped from the analysis as it is a very small sector, with few observations, and often a strong outlier in terms of labour productivity. Given that the measurement of productivity in the public sector can be challenging, the regressions have also been run while excluding the public sector. The results remain broadly robust.

¹⁸ See Eurostat variables nama_10_a10 and name_10_a10_e

¹⁹ This difference between the coefficients of literacy and numeracy skills is statistically significant. The difference between the respective coefficients on literacy and problem solving skills is not statistically significant.

²⁰ See also Flabbi and Gatti (2018) for a recent discussion of the challenges underlying the measurement of the causal impact of human capital on economic performance.

²¹ Notably, coefficients lose significance when additional sector-level controls are included in the regression.

²² The PIAAC dataset also includes a number of pre-calculated non-cognitive skills indicators (*Influence*, *Readiness to learn*, *Planning*, *Task discretion*). Our results on non-cognitive indicators are broadly robust to using these indicators instead of ours. See e.g. Liu and Fernandez (2018) for analysis using these non-cognitive skills indices.

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