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# Which skills for the digital era? Returns to skills analysis

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# *WHICH SKILLS FOR THE DIGITAL ERA? RETURNS TO SKILLS ANALYSIS*

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## *ABSTRACT*

*This paper sheds light on the extent to which different types of skills are rewarded as industries go digital. It relies on information from the OECD Survey of Adult Skills on labour market participation and workers' skills for 31 countries as well as on a novel OECD index on the digital penetration of industries. It investigates how cognitive and non-cognitive skills are rewarded in digital vs. less digital intensive industries and assesses the extent to which skills bundles matter. The results indicate that digital intensive industries especially reward workers having relatively higher levels of self-organisation and advanced numeracy skills. Moreover, for workers in digital intensive industries, bundles of skills are particularly important: workers endowed with a high level of numeracy skills receive an additional wage premium, if they also show high levels of self-organisation or managing and communication skills.*

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# *Executive Summary*

This study explores how the digital transformation is affecting the demand for skills in 31 countries, by analysing how skills are rewarded in sectors which are more or less digitally intensive. In so far as higher salaries reflect relative skills shortage, returns to skills contribute to inform on how the demand of different skills is met by labour market supply.

The analysis differs from previous studies in several ways. First, it investigates the returns to different types of skills, both cognitive skills, i.e. skills acquired through education such as literacy, numeracy and problem solving, and non-cognitive skills and personality traits, which are measured using information about the tasks that workers perform on the job. Special emphasis is devoted to: information and communication technologies (ICT)-related skills; advanced numeracy skills; managing and communication skills and self-organisation; readiness to learn and creative problem solving.

Furthermore, the study addresses the important question of skill complementarities and investigates whether and to what extent cognitive and non-cognitive skills are demanded together. As different technologies display different degrees of complementarity (or substitutability) to different types of skills, the study explores how the multidimensionality of skills relates to the digital transformation. In the presence of skill complementarities, the labour market rewards such bundles more than individually considered skills.

Third, the study highlights how returns to skills differ across digitally intensive and less digitally intensive sectors, thanks to a new taxonomy of sectors by their degree of digital transformation. The taxonomy takes into account some of the many facets that the digital transformation may take, and in particular its technological component, its human capital requirements, and new forms of market access in the digital era.

The analysis is carried out on data from the Programme for the Assessment of Adult Competencies (PIAAC). This extensive survey covers 31 OECD countries and partner economies and provides a wealth of information about workers' skills, the tasks they perform on the job, and their workplace, among others. The rich set of individual-level information available makes it possible to estimate the role of skills in determining wages with accuracy and minimising measurement errors.

The findings indicate that cognitive as well as non-cognitive skills are strongly rewarded by labour markets, even when controlling for industry and occupation fixed effects, and other characteristics of the individual worker (including education). Furthermore, digital intensive industries especially reward workers having relatively higher levels of self-organisation and advanced numeracy skills. Also, for workers in digital intensive industries, bundles of skills are particularly important: workers endowed with a high level of numeracy skills receive an additional wage premium, if they also show high levels of self-organisation or managing and communication skills.

The results in the present study can contribute to design effective and forward-looking skills and employment policies, aimed at aligning labour market demand and supply and helping workers to succeed in the digital era.

# *WHICH SKILLS FOR THE DIGITAL ERA? RETURNS TO SKILLS ANALYSIS*

## Introduction

Digitalisation is changing jobs the way we know them and is disrupting labour markets. Some jobs are being offset by automation, others see their nature and tasks change, while new jobs emerge as the digital revolution unfolds. As the content and nature of jobs change, so do the skills required to perform them: this shapes labour supply and demand, employment patterns and the demand of skills associated to jobs, both existing and new.

It thus becomes important to understand what type of skills workers need as the digital transformation unfolds, affecting production and the task-content of occupations. To answer this question, the present study investigates how different types of skills, i.e. cognitive as well as non-cognitive skills and personality traits, are rewarded by labour markets. In so far as higher salaries reflect relative skills shortage, returns to skills contribute to inform on how the demand of different skills is met by labour market supply.

In particular, this study assesses whether returns to skills differ between industries that are more digitally intensive, as compared to those that have undergone the digital transformation to a lesser extent. Higher returns in digital intensive industries help identify those skills that are in high demand in jobs that are more exposed to the digital transformation, and may represent a much needed complement to the deployment of digital technologies at the workplace. Furthermore, the paper addresses the important question of skill complementarities. It investigates whether and to what extent cognitive and non-cognitive skills are complementary, and if these complementarities differ in digital as opposed to less digital intensive industries.

The analysis is carried out on data from the Programme for the Assessment of Adult Competencies (PIAAC). This extensive survey covers 31 OECD countries and partner economies and provides a wealth of information about workers' skills, the tasks they perform on the job, and their workplace, among others. The rich set of individual-level information available makes it possible to estimate the role of skills in determining wages with greater accuracy than done in the past. What is more, as workers' cognitive skills (namely literacy, numeracy and problem solving in technology rich environments) are assessed through externally assessed tests, using PIAAC allows containing possible mismeasurement issues. In addition, using PIAAC information on the tasks that workers perform on the job allows shedding light on workers' 'endowment' of other types of skills which may be relevant on the job, such as non-cognitive and social skills, as well as some of their personality traits.

This study builds on Grundke et al. (2017a), who use state-of-the-art factor analysis to extract six task-based skill indicators. This makes it possible to investigate the returns to both cognitive skills, i.e. skills acquired through education such as literacy, numeracy and problem solving, and to non-cognitive skills and personality traits, which are measured using information about the tasks that workers perform on the job. Special emphasis is devoted to: information and communication technologies (ICT)-related skills; advanced numeracy skills; non-cognitive skills such as managing and communication and self-organisation; and socio-emotional skills such as readiness to learn and creative problem solving (see Grundke et al. 2017a, for details). The analysis thus complements previous studies by proposing first-time estimates of the returns to these task-based skills using a rich cross-country dataset and controlling for country, industry and occupation specificities as well as for the cognitive skills of workers.

The task-based approach pursued here follows in the steps of recent analyses highlighting the role of tasks carried out on the job in shaping the demand for labour and its returns (e.g. Acemoglu and Autor, 2011; Firpo et al., 2011; Acemoglu and Autor, 2012; Autor and Handel, 2013). In particular, evidence suggests that since the 1980s computerisation has had a non-linear effect on wages by skill: it has negatively affected the earnings of workers in the middle of the skill distribution, while positively affecting those at the high and low end of the skill distribution. An explanation often offered in this respect is one whereby medium skilled workers carry out relatively more routine and non-interactive tasks which are at higher risk of technology-driven automation (e.g. Acemoglu and Autor, 2011). Furthermore, recent evidence suggests that human capital is highly specific to the tasks carried out by workers, and less so to the occupation, industry or the firm the individual works in (Gibbons and Waldman 2004, Poletaev and Robinson 2008, Gathman and Schoenberg 2010).[1] Closest to the approach taken here is the work by Firpo et al. (2011), where the returns to cognitive skills and tasks are separated, and wages are allowed to differ across occupations, even conditional on skills and tasks (as opposed to, e.g. Acemoglu and Autor, 2011). Thus, by being able to disentangle the effects of task-based skills from the ones of cognitive skills and of occupation, industry and firm specificities, this study provides new evidence about human capital being highly specific to the tasks carried out by individuals.

To the best of the authors’ knowledge, this is the first study investigating returns to skills for a substantial number of countries and in light of the digital transformation. To this end, the analysis exploits a taxonomy of sectors reflecting the degree to which sectors have been permeated by the digital transformation (see Calvino et al., 2018, for details). This taxonomy takes into account some of the many facets that the digital transformation may take, and in particular: its technological component (proxied by a sector’s intensity in ICT investment, purchases of intermediate ICT goods and services, and robots); its human capital requirements (i.e. ICT specialists); and one of the new forms characterising market access in the digital era, namely e-commerce. By relying on this novel OECD index, this study is able to evaluate how the digitalisation of industries shapes the demand for different types of skills, both cognitive and non-cognitive.

Lastly, as different technologies display different degrees of complementarity (or substitutability) to different types of skills, accounting for the multidimensionality of skills in the labour market is essential to portray the opportunities and challenges that the digital transformation imposes on production in OECD countries and partner economies . To this end, the present analysis investigates the complementarities that might exist between certain types of skills, and whether these complementarities differ depending on the extent to which the digital transformation has permeated different sectors. In the presence of skill complementarities, the labour market should reward workers that show relatively higher levels of both of these skill types jointly, and reward such bundles more than individually considered skills. Such an analysis further allows to shed light on skill bundles and whether certain skill bundles are particularly important for digital intensive industries.

In what follows, a brief overview of relevant studies is accompanied by a description of the data used in the analysis and of the empirical strategy pursued. A review of main results follows, and precedes some preliminary conclusions.

## Literature Review

### Skills and technological change

The so-called 'skill-biased technological change' hypothesis argues that technical progress manifests itself in a soaring demand for high skilled workers (i.e. college graduates) relative to low skilled workers (i.e. those with no college degree). Returns to skills are supposed to increase when the supply of skilled workers is not sufficient to cover the increased demand triggered by technological change. This leads to higher wage premia in the high end of the skill distribution and causes a rise in wage inequality (Katz and Murphy 1992; Kruger 1993; Card and Lemieux, 1994; Acemoglu, 1998; Autor, Katz, and Krueger, 1998; Chennells and Van Reenen 1998; Machin and Van Reenen 1998; Card and DiNardo 2002; Goldin and Katz, 2008).

While representing a key contribution to a better understanding of the way technology shapes labour markets, skill-biased technological change cannot account for the non-monotone employment growth observed along the skill distribution. Evidence in fact suggests that the share of jobs with an intermediate level of skills has grown at a much lower rate than that of high-skilled or low-skilled jobs. This so-called 'job polarisation' has been affecting the wage distribution, too. Several studies have taken a task perspective in describing the returns to working in a given occupation, conditional on skills: Acemoglu and Autor (2011) and Acemoglu and Handel (2013) build on Roy (1951) and propose a model where occupations differ by the bundles of tasks which workers must perform simultaneously. According to this literature, as computers substitute workers in routine tasks and complement workers in more complex, non-routine tasks related to problem-solving or communication, workers will continue to perform the tasks for which they have a comparative advantage, compared to computers, conditional on labour supply and product demand elasticities (Autor, 2015).[2]

While both skill- and routine- biased technical change approaches concur with the view that the observed rising wage inequality is attributable to technological progress, differences in the mechanisms held accountable for such labour market dynamics have sparked lively debates about what skills are needed for workers to cope with the increasing digitalisation of their work places. Disentangling the multifaceted effects of digitalisation on a vast array of occupations and industries thus becomes essential to inform policy about the skills that workers need the most to cope with and thrive as production goes digital.

Two additional strands of the literature also appear relevant for the analysis. While the role of cognitive skills for digitalisation has received much attention, the importance of non-cognitive skills has thus far been mostly overlooked, with few notable exceptions (e.g. Deming, 2015). Non-cognitive skills can conversely contribute to explain the large unexplained variations of wage differences (e.g. in Deming and Kahn, 2017). Furthermore, as non-cognitive skills strongly correlate with both ICT-cognitive skills and earnings, disregarding non-cognitive skills may bias results due to endogeneity (Gintis and Osborne, 2001; Ingram and Neumann, 2006). Another group of studies focuses technologies, but also in the way e.g. communication and managerial organisations operate (Bresnahan et al., 2002). This is an aspect that cannot be neglected.

## Returns to skills

Existing studies assessing the returns to different skill sets in the context of digitalisation highlight the importance of computer use at work, especially in technology-advanced industries, and its effect on business activities. Word processing, spreadsheets, and databases improve workplace efficiency, and information and communication devices provide a wide range of opportunities, including reaching out to new markets (Dolton and Pelkonen, 2008).

Krueger (1993) pioneered the literature on the return to computerisation skill and showed that, in the 1980s in the United States, individuals using computers at work earned 10% to 15% higher wages. Moreover, occupations that use computers more intensively also displayed higher than average wage growth rates, implying that the fast diffusion of computers at work does not offset the wage premium of these occupations. DiNardo and Pischke (1997) were the first to highlight the endogeneity of computer use by comparing the use of computers with the one of other office material, including calculators, telephones, pens or pencils. They conclude that the high returns to computerisation found earlier are possibly due to selection bias, which mainly comes from two sources: first, workers who use computers at work also possess other unobserved, but highly rewarded, skills; second, computers tend to be introduced in higher paid occupations.

More recent work correcting for endogeneity does not question the positive link between computer use and wages, but argues that this positive link depends on the nature of the tasks being performed with computers. Autor, Levy and Murnane (2003) provide evidence that the effect of computerisation on labour demand depends on the extent to which tasks can be automated. They argue that computerisation reduces the demand for labour input of routine manual and routine cognitive tasks, while increasing the demand for labour input of non-routine cognitive tasks. Along the same line, Borghans and ter Weel (2003) find evidence for the returns to computers only accruing to those with highest level of use sophistication. Dolton and Pelkonen (2008) show a small return to the use of the “office IT function”.

In addition to computerisation, the set of positive determinants of earnings in advanced economies include other cognitive skills. Hanushek et al. (2015) and Falck et al. (2016) both employ the PIAAC dataset to look at the returns to cognitive skills: numeracy (Hanushek et al., 2015), and problem-solving in technology-rich environments (Falck et al., 2016). Both studies find strong returns to numeracy skills and problem-solving skills across OECD countries. However, these analyses suffer from their inability to directly address the role of non-cognitive skills, which biases their results. The present work not only highlights which cognitive and non-cognitive skills are seemingly important for digitalisation, but also on which combinations of cognitive and non-cognitive skills are key in digital environments. Doing so, our results contribute to a group of studies focusing on the complementarity of cognitive and non-cognitive skills.

## Cognitive and non-cognitive skills

While many argue that social skills and personality traits are the most important determinants of earnings (e.g. Heckman et al, 2006; Heckman and Kautz, 2012; Lindqvist and Vestman, 2011), empirical evidence on which social skills and personality traits are most rewarded in digital environments is scant, and usually focused on one personality trait only. Bowles et al. (2001) argue that when earnings are raised due to technological advancements, individuals endowed with certain types of personality traits, such as an individual’s rate of time preference, and sense of personal efficacy, may benefit more than others. Bresnahan et al. (2002) look more closely at the technological process itself and provide firm level empirical evidence that technology changes management and organisation at the workplace, and raises the demand for organisation-related skills in firms, including flexibility and autonomy.

Cubel, et al. (2016) use a laboratory experiment to detect which personality traits among the "Big Five" are rewarded in the labour market, because they enhance the productivity of workers.[3] They conclude that conscientiousness plays a major role in an individual’s performance. Regarding social skills and their complementarity to cognitive skills, Weinberger (2014), Deming (2015) and Deming and Kahn (2017) show that labour market returns are higher when individuals combine good levels of cognitive and social skills. In addition, Deming (2015) finds that these complementarities are stronger in jobs that are more intensive in the use of ICT.

While relating to the above findings, our approach improves the analysis along several dimensions. First it addresses the challenging task of more precisely measuring social skills and personality traits (Borghans et al., 2011). Compared to previous measures of social skills obtained on the basis of surveys or laboratory experiments, our skill indicators are constructed using information about the tasks performed at the workplace. As such, they more accurately capture the social skills relating to productivity. This study is also linked to the literature on the task-specificity of human capital, which argues that human capital is highly specific to the tasks carried out by workers, and less so to the occupation, industry or the firm individuals work in (Gibbons and Waldman 2004, Poletaev and Robinson 2008, Gathman and Schoenberg 2010). By disentangling the effects of task-based skills from those of cognitive skills and of occupation, industry and firm specificities, this study provides further evidence about human capital being highly specific to the tasks carried out by individuals (as e.g. Deming and Kahn, 2017).

## Data and Empirical Strategy

### Data

The OECD Survey of Adult Skills (PIAAC) is an international survey of individuals that is representative of the population between the age of 16 and 65. Data collection was completed in 2011-12 for the first round (22 OECD countries and the Russian Federation, OECD, 2013) and in 2014-2015 for the second round (6 OECD countries, plus Singapore and Lithuania, OECD, 2016). The analysis in this paper includes both rounds of PIAAC to be able to shed light on the skills patterns of as many countries as possible. The database contains information on 208 620 individuals of which 138 605 were employed at the time of the interview. From the present analysis are excluded unemployed individuals and individuals who did not report information on the main observable outcomes of interest, i.e. wages and skills. This reduces the size to 104 296 individuals. Unless otherwise specified, all descriptive statistics and empirical estimates are re-weighted using population weights.

The main purpose of the OECD Survey of Adult Skills is to test the cognitive skills of adults along three dimensions: literacy, numeracy and problem solving in technology rich environments. In addition, the survey provides information on the frequency of the performance of several tasks including reading, writing, numeracy, ICT and problem solving, partially matching the set of cognitive skills assessed through the tests. It also includes information on the frequency of the performance of other types of tasks such as those related to management, communication, organisation and planning, and physical work. Moreover, PIAAC gives information on workers' attitude towards learning, trust, health and other issues, which are gathered through self-reported assessments. Grundke et al (2017a) use this additional information on the tasks that workers perform on the job as well as the self-reported information on workers' attitudes and personality traits to conduct an exploratory factor analysis and extract six skill indicators that capture different types of cognitive, non-cognitive and social skills of workers.

As the analysis in this paper aims to encompass both cognitive and non-cognitive skills, the measures for cognitive skills from PIAAC are combined with the measures for non-cognitive and social skills from Grundke et al. (2017a). These six skill indicators and the items of the PIAAC background questionnaire on which they build are presented in Table 1. The six skill indicators mirror: information and communication technologies (ICT)-related skills; advanced numeracy skills; accountancy and selling skills; non-cognitive skills such as managing and communication and self-organisation; and socio-emotional skills such as readiness to learn and creative problem solving (see Table 1).

The PIAAC Survey also gathers information on the salaries and bonuses earned by individuals in the year prior to the survey year, as well as information on the industry, occupation and size of the firm individuals works in, as well as a number of socioeconomic background characteristics for these individuals (e.g. educational attainment, age, gender, etc.). Contrary to PIAAC public use data, which for some countries only report the deciles of the country-specific earning distribution an individual receives, the dataset used in the present study reports an individual's gross hourly earnings and expresses them in purchasing power parity terms. For some individuals with missing hourly wages, a value is imputed on the basis of the reported monthly gross salary and bonuses, and the number of hours worked by the individual in the last month. Both hours worked and hourly wages have been cleaned of outliers by trimming the top and bottom 1% of their respective distribution.

The analysis in this study further relies on a measure of the digital intensity of industries developed by Calvino et al., 2018 and which takes into consideration the technology (i.e. proportion of investment which is in ICT; purchases of ICT intermediate goods and services as a percentage of output, robots per employee), human capital requirements (i.e. ICT specialists as a proportion of total employment in the sector), and market scope (i.e. e-sales as a proportion of total industry sales) sides of digitalisation. A single metrics combining all these aspects is used to rank 36 2-digit ISIC4 sectors. Depending on their rank, which mirrors the extent to which industries have been penetrated by the digital transformation, industries are subdivided into digital vs less digital intensive ones, using the median and the discriminant.[4] Due to data constraints, this taxonomy at present does not rely on information about e.g. industries' reliance on frontier technologies such as 3D printing or machine learning. However, the complexity and comprehensiveness of the information set underlying this exercise should suffice to provide a faithful representation of how sectors are being transformed by digitalisation.

**Table 1. Indicators of job-related task and skill requirements**

| Indicator of job related skill requirements | Items included in the construction of the indicator |
|---|---|
| ICT Skills | G_Q05e Frequency of excel use |
| | G_Q05g Frequency of programming language use |
| | G_Q05d Frequency of transactions through internet (banking, selling/buying) |
| | G_Q05a Frequency of email use |
| | G_Q05c Frequency of simple internet use |
| | G_Q05f Frequency of word use |
| | G_Q05h Frequency of real-time discussions through ICT Computer |
| | G_Q01b Frequency of Reading letters, emails, memos |
| | G_Q02a Frequency of Writing letters, emails, memos |
| | G_Q06 Level of Computer Use required for the job |
| | F_Q06b Frequency of working physically over long periods |
| Readiness to learn and creative problem solving | I_Q04j I like to get to the bottom of difficult things |
| | I_Q04m If I don't understand something, I look for additional information to make it clearer |
| | I_Q04h When I come across something new, I try to relate it to what I already know |
| | I_Q04b When I hear or read about new ideas, I try to relate them to real life situations to which they might apply |
| | I_Q04d I like learning new things |
| | I_Q04l I like to figure out how different ideas fit together |
| Managing and Communication | F_Q04b Frequency of negotiating with people (outside or inside the firm or organisation) |
| | F_Q03b Frequency of planning activities of others |
| | F_Q02b Frequency of instructing and teaching people |
| | F_Q02e Frequency of advising people |
| | F_Q04a Frequency of persuading or influencing others |
| Self-Organisation | D_Q11a extent of own planning of the task sequences |
| | D_Q11b extent of own planning of style of work |
| | D_Q11c extent of own planning of speed of work |
| | D_Q11d extent of own planning of working hours |
| Accountancy and Selling | G_Q01g Frequency of Reading financial invoices, bills etc. |
| | G_Q03b Frequency of Calculate prices, costs, budget |
| | G_Q03d Frequency of using calculator |
| | F_Q02d Frequency of client interaction selling a product or a service |
| Advanced Numeracy | G_Q03f Frequency of preparing charts and tables |
| | G_Q03g Frequency of Use simple algebra and formulas |
| | G_Q03h Frequency of Use complex algebra and statistics |

*Source*: Grundke et al. (2017a), based on PIAAC.[5]

## Empirical Strategy

This paper assesses the returns to different types of skills by estimating individual level wage regressions on data from PIAAC. Differently from Hanushek et al. (2015) and Falck et al. (2016) who also do so, the present study is the first to include measures of task-based skills based on Grundke et al. (2017a). This is important for two reasons, one policy-related, the other technical. On the one hand, markets reward cognitive as well as non-cognitive skills, and policy needs being informed about labour market returns to non-cognitive skills to be able to design suitable education and training policies. On the other hand, the presence of an extra set of controls reduces the extent to which possible omitted variables may bias our estimates. It is also important to note that the present study proposes a first-time assessment of skill premia in digital vs less digital intensive industries.

The estimated individual-level wage regressions investigate whether the following skills are complementary to the digitalisation of the workplace: the cognitive skills numeracy and literacy[6]; the task based skills ICT, managing and communication, accountancy and selling, self-organisation and advanced numeracy skills; and the personality trait readiness to learn and creative problem solving.

The empirical hypothesis underlying the analysis is that sectors that are more digital intensive should reward workers' skills differently, and possibly more (assuming equal supply of skills across sectors), than sectors that have been penetrated to a lower extent by the digital transformation. This, of course, conditional on other worker-specific observable characteristics, and other controls which are specified below. Such a hypothesis has its roots in the "canonical" model of human capital in Goldin and Katz (2008), where technological progress raises the demand for skill. When demand for human capital expands faster than its supply due to technological progress, inequality of wages across skill classes rises, too. As some of the above-mentioned skills are easier to supply than others, the returns to skills in the whole economy are expected to vary with the type of skill considered. If one assumes that advanced numeracy skills are harder to shape than, e.g. managing and communication ones, or if they are rarer among workers, one should expect the market to offer a higher premium for advanced numeracy than for managing and communication skills.

In addition, workers with different skills may be carrying out different tasks, which in turn may have different degrees of complementarity with technology (e.g. Acemoglu and Autor, 2012). As a consequence, it is expected that the wage returns differ not only across type of skills, but also between digital and less digital intensive sectors. While it would be natural to expect that digital intensive sectors reward the same skill more than less digital intensive ones,[7] a task-based perspective would allow for the existence of non-linearities in the way skills are rewarded relative to the technological endowment of firms and sectors. Occupational polarisation, for example (Autor et al., 2006; Acemoglu and Autor, 2011), is associated with higher wages of individuals both at the top and bottom of the skill distribution until the beginning of the 2000s. This happened since these types of workers both carry out tasks which cannot be substituted by computers and rising income sustained the demand for manual tasks. In the last decade, instead, the wages of individuals at the bottom of the skill distribution decreased more than those of middle- and high-skilled individuals, as workers previously performing routine-intensive tasks were displaced by computerisation and entered manual task-intensive occupations (Autor, 2015). Given the above, the sign of the difference in skill returns between digital and less digital intensive sectors remains ex-ante ambiguous.

These hypotheses are tested on the pooled sample of the working population of all 31 PIAAC countries, based on the following empirical specification:

$$\log(wage)_i = \alpha_0 + \alpha_1 DigInd_k + DigInd_k * \boldsymbol{skills_i \beta} + \boldsymbol{skills'_i \gamma} + \boldsymbol{x'_i \delta}$$
$$+\boldsymbol{\mu_c} + \boldsymbol{\sigma_{Tiva18}} + \boldsymbol{\rho_{isco08}} + \boldsymbol{u_i} \qquad (1)$$

for individual i.

The dependent variable is the log of the gross hourly wage in USD (including bonus payments).[8] The dummy variable *DigInd* indicates whether an individual *i* works in a digital intensive industry. 2-digit ISIC rev.4 industries are defined as digital intensive if they display a higher digital intensity than the median among all 36 industries (across countries[9]). The dummy variable for digital intensive industry is interacted with each of the skill variables (i.e. the vector skills), namely: numeracy, literacy,[10] ICT, managing and communication, accountancy and selling, self-organisation, advanced numeracy skills, and readiness to learn and creative problem solving.

The coefficients of interest are captured by the vector $\beta$, which includes the coefficients of the interaction of the digital industry dummy variable and all the skill variables considered. A positive and significant coefficient in the vector $\beta$ indicates that individuals working in a job in a digital intensive industry are additionally rewarded by labour markets for the specific skill under consideration, compared to the same jobs being performed in less digitalised industries. This would imply that the use of digital technologies and the skill under consideration are complements in the production process and signal the need for workers to acquire those skills to cope with the increasing digitalisation of their workplaces.

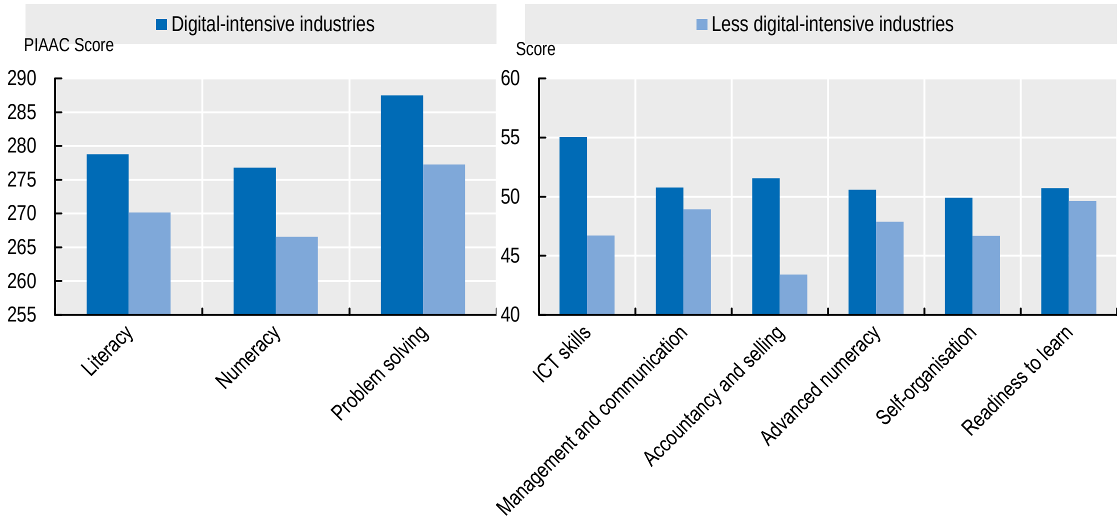
The vector *x* includes additional covariates at the worker's level, namely: age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works in (either medium sized firm, defined as having 51-250 employees; or large firm, having more than 250 employees, the comparison group being small firms, defined as firms with up to 50 employees[11]), a dummy variable for whether the individual works less than 21 hours a week (to account for possible part-time-related patterns), as well as two dummy variables for the state of health of the individual (good and very good health, the comparison group being poor health). Fixed effects for countries (μ), for 18 aggregated industries (σ) (TiVA 18 industry list)[12] as well as for ISCO08-one digit occupations (ρ) are also included to control for unobserved wage determinants at the country, industry and occupation level.[13] All specifications are estimated by weighted OLS using individual senate weights, which are based on the population weights included in the PIAAC data set and ensure that each country is given the same weight in the regression. Standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance one for the pooled sample using senate weights to weight observations from single countries.

While advancing the returns to skills discussion in many ways, the present analysis nevertheless does not treat the endogeneity of sectors explicitly, at least in this first stage. However, the high degree of consistency of results across specifications buttresses the importance of selected cognitive and non-cognitive skills for wage determination, and how these differ between digital and less digital intensive sectors.[14]

## Results

In what follows, some first descriptive statistics shed light on the skill endowment of workers in digitally-intensive and less digitally intensive industries. Figure 1, which relies on data from 31 OECD countries and partner economies , shows that workers in digital-intensive industries on average exhibit higher levels of cognitive as well as non-cognitive skills and social skills than workers in less digitally-intensive sectors of the economy. This may of course depend on the type of workers employed in digital vs less digital intensive sectors, with the latter being generally more intensive in unskilled workers.

**Figure 1. Average skill levels in digital and less digital intensive industries across 31 OECD countries and partner economies, 2012 or 2015.**




*Note*: All task-based skill indicators are rescaled to the interval 0-100. The assessed cognitive skills are measured in PIAAC scores ranging from 0 to 500. Averages across countries are computed given the same weight to each country. All differences in skill means between digital and less digital intensive industries are significant at the 5% level.
*Source*: Authors' own compilation on data from PIAAC and other sources.

## Skills are better rewarded in digital intensive sectors

To try and isolate the “true” role of working in a digital intensive sector on skills and skill returns, in what follows the estimates control for some of the individual-level determinants which could drive this difference in skill intensities across sectors. In practical terms, this analysis answers the question of which skills are important for the digital transformation by investigating which type of skills are in short supply and/or high demand and therefore command a wage premium in digital vs. less digital intensive industries. Table 2 presents the results for the baseline specification (1), i.e. an individual level wage regression that includes the interaction terms of a dummy variable for working in a digital intensive industry with each of the skill types considered, the skill variables themselves, as well as a number of individual-level controls, such as a worker’s age, gender and education.[15] The use of PIAAC and in particular of workers’ scores in the assessed cognitive skill test, helps controlling for workers’ ability, which, while often being unobserved, clearly determines individual wages.

Table 2 shows that for two types of skills, labour market returns are higher in digital intensive industries than in less digital intensive industries. These are advanced numeracy skills and self-organisation skills. These skills therefore seem to be relatively more valued in digital intensive sectors, thus commanding a premium in salary or bonuses. This may depend on workers in digital intensive industries needing to operate in a more independent and decentralised fashion (e.g. through telework), to perform relatively more non-routine tasks, to be better matched with the tasks to be carried out, or to having to deal with continuously changing settings for which technical skills coupled with self-organisation skills are increasingly important.

These results are robust to a number of checks. In Table A2, each interaction term enters the specification alone (rather than introducing all interaction terms at the same time, as in Table 2). The results show that all type of skills are better rewarded in digital intensive industries, in particular advanced numeracy skills, self-organisation skills, ICT skills and numeracy. However, in these specifications the estimated coefficients for the skill variables are clearly biased upwards by the omission of all other skill variables, which are correlated with the individually included skill. The results in Table 2 are robust to defining digital intensive industries as the top quartile instead of the top 50% of the 36 industries according the ranking in Calvino et al. (2018), as shown in Table A3, column 2.[16]

Importantly, the results in Table 2 are not driven by the occupational category workers belong to.[17] If occupational controls were missing, and if digital intensive sectors featured more workers in occupations which are on average better paid than those in less digital intensive sectors, the skills coefficients and the interaction coefficients with the digital intensive sector dummy would be biased, as they would capture the contribution of occupational compositions to wage dynamics. However, results where these occupation fixed effects are excluded - and which are therefore driven by cross-occupational differences between digital and less digital intensive sectors-, are very similar to the baseline results (Table A3, column 4). The same holds true for excluding sectoral fixed effects (column 5), which are present in the baseline specification. Table A3, column 3 is even more demanding than the baseline specification, and includes country-aggregated industry (18 TiVA industries) fixed effects. These make sure that the main coefficients of interest are not driven by country-industry specific characteristics such as e.g. wage bargaining institutions, average industry productivity, innovation or capital intensity, as well as specific industrial and innovation policies.

By showing that the reward of skills goes beyond the occupation or even the sector of employment, the above results reinforce the intuition that such rewards are linked to features of the firms where individuals work, including more effective communication, organisational structure or matching of workers and capital; better monitoring ability; implementation of profit sharing or efficiency wages; etc. Song et al. (2015), for instance, report that the increase in the variance of individual earnings in the U.S. between 1978 and 2013 was driven by between-firm inequality much more than by within-firm inequality. However, because the specification controls for the size of the firm, such firm specificities may only explain the strong returns to skills, if the variation of firm characteristics within firms of similar sizes is large and if these are correlated with workers' skills.

**Table 2. Returns to skills in digital vs. less digital intensive industries**

| | |
|---|---|
| Digital Sector Dummy | 0.040*** |
| | (0.010) |
| ICT Skills | 0.087*** |
| | (0.009) |
| Management and Communication Skills | 0.041*** |
| | (0.005) |
| Accountancy and Selling Skills | -0.027*** |
| | (0.004) |
| Advanced Numeracy Skills | 0.010** |
| | (0.004) |
| Self-Organisation Skills | 0.021*** |
| | (0.003) |
| Readiness to Learn | -0.005 |
| | (0.004) |
| Literacy | 0.007 |
| | (0.006) |
| Numeracy | 0.041*** |
| | (0.009) |
| (Digital Sector)X(ICT Skills) | 0.002 |
| | (0.010) |
| (Digital Sector)X(Management and Communication Skills) | 0.002 |
| | (0.006) |
| (Digital Sector)X(Accountancy and Selling Skills) | 0.004 |
| | (0.006) |
| (Digital Sector)X(Advanced Numeracy Skills) | 0.018*** |
| | (0.006) |
| (Digital Sector)X(Self-Organisation Skills) | 0.015*** |
| | (0.005) |
| (Digital Sector)X(Readiness to Learn) | -0.004 |
| | (0.004) |
| (Digital Sector)X(Literacy) | -0.001 |
| | (0.007) |
| (Digital Sector)X(Numeracy) | 0.011 |
| | (0.008) |
| Control Variables | Yes |
| Observations | 104 296 |
| Adjusted R-squared | 0.576 |

*Note*: The dependent variable is the log of hourly wages. In addition to the shown covariates, the specification also includes age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specification is estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).
*Source*: Authors' own compilation on data from PIAAC and other sources.

In consideration of the task-based nature of the five task-based skill indicators used in the present analysis, the results in Table 2 also contribute to the recent literature on the task-specificity of human capital (Gibbons and Waldman 2004). The fact that even when controlling for industry and occupation fixed effects, individual control variables (including education) and firm size, the returns to task-based skills are still in the same ballpark than those for cognitive skills constitutes strong evidence about the importance of task-specific human capital for production and labour markets. Wage returns to ICT skills are twice as big as those related to numeracy skills, whereas management and communication skills are rewarded as much as numeracy skills are. These results also indicate the importance for workers to adequately use their skills and human capital on the job. This in turns calls for workers to be well matched to tasks they perform on the job and stresses the importance of good human resource and organisational management within firms.

In Gibbons and Waldman (2004), the worker is rewarded for the human capital it cumulates on the job, which is a function of the tasks she performs. If tasks for the same individual were different between digital and less digital intensive sectors (e.g. because different technologies are embedded in production), the worker would be rewarded differently for her skills in the two types of sectors. This is exactly what the results in Table 2 suggest for Self-Organisation and advanced numeracy skills. However, unfortunately the dataset on which estimates rely does not allow to move beyond speculation on this point, as one can only control for the size of the firm or entity. Future work will try to explore possible ways to account for firm heterogeneity in sectors, and further investigate the robustness of the results presented so far.

## Workers in digital intensive sectors are generally better paid

Table 2 also reports the coefficient for the dummy variable which identifies individuals working in a digital intensive industry. Even when controlling for all types of skills, occupation specific characteristics, aggregated industry characteristics and country characteristics, the size of the firm and all the other individual control variables, workers in digital intensive industries still appear to earn 4% higher wages than comparable workers in less digital intensive industries. The positive selection of better skilled workers into digital intensive industries is ruled out by that fact that we control for various types of workers' skills.

As Table A3 shows, even when controlling for all country-specific aggregated industry characteristics the significant positive effect of digitalisation on wages persists (ruling out many explanations, e.g. related to bargaining institutions or industrial policy provisions). One possible driver of these associations is the fact that more digitalised industries are populated by more productive firms, and can therefore reward their workers better. Digital intensive sectors may also be characterised by higher concentration and market power. If this translates into greater profits and companies are willing to distribute them, at least partially, to their workers, digital intensive sectors could be paying a higher wage than less digital ones. It is finally possible that companies in more digital intensive sectors are more willing to pay a premium to motivate workers and avoid (excessive) labour turnover, which can be disruptive for production and raise the risk of knowledge spill overs to competitors.

Unfortunately, as mentioned, the PIAAC dataset does not allow controlling for a host of firm characteristics (aside for size) which may be playing a role in the wage setting and which are correlated to the adoption of digital technologies. However, future work will try to further investigate the mechanisms explaining higher wages in digital intensive industries by exploiting alternative data sources.

## Bundles of skills bear extra rewards

On the basis of the results shown above and of the skills complementarity hypothesis, one may ask whether a certain type of skills gets rewarded not only because of its intrinsic usefulness in production, but also because of its synergies with other skills. Grundke et al. (2017b), empirically testing Ohnsorge and Trefler (2007), already shows that the distribution of skill mixes at the worker level (as they are defined here) contributes to shaping industry competitiveness and positioning in global value chains. Also, it is in principle possible that some skills are not valued per se by the market, but only in combination with other skills. This would be the case if one skill is relatively abundant in the population (relative to the demand for it), but it is hardly available in combination with another skill, whereas both are needed by the same worker for production purposes.

In such cases, companies may be willing to reward these bundles differently, depending on the technology embedded in production. As a consequence, the return to skill mixes may be different between digital and less digital intensive sectors. A review of the relevant literature, however, fails to yield clear expectations for the sign of the possible correlations between each skill mix and wages, both in the whole economy and in digital intensive sectors. Only Deming (2015), who uses data on cognitive and non-cognitive skills for workers in the U.S., finds that in ICT intensive jobs bundles of cognitive and non-cognitive skills are better rewarded.

In what follows, the analysis is expanded to consider skills "in bundles", so as to shed light on the possible complementarities that exist between different types of skills. Complementarities are investigated for three types of skills which are expected to be in high demand in digital intensive sectors (ICT skills, advanced numeracy, and numeracy), and all other skills. To this end, specification (1) is estimated for the sub-samples of digital and less digital intensive industries respectively. The interaction terms of the digital intensive industry dummy with each skill in equation (1) are replaced by the interaction of one specific skill with each of the other skill types.

Overall, results indicate that for workers in digital intensive industries the bundling of different types of skills is particularly important. Table 3 investigates the complementarities that exist between ICT skills and all other types of skills for digital vs. less digital intensive industries. Results show that whereas in less digital intensive industries no skill complementarities exist between ICT skills and other skills, in digital intensive industries ICT skills are rewarded more when bundled with self-organisation skills. Table 4 conversely investigates the complementarities that may exist between advanced numeracy skills and all other types of skills for digital vs. less digital intensive industries. Whereas in less digital intensive industries no skill complementarities exist between advanced numeracy skills and other skills, in digital intensive industries advanced numeracy skills seem to be complementary to self-organisation skills and to management and communication skills. Table 5 finally shows that similar complementarities are found when using the assessed cognitive skill numeracy instead of the task-based skill advanced numeracy, which is measured using information on job tasks. This is true conditional on the occupation and the industry in which workers are employed, as well as all the other control variables.

This evidence can be rationalised when considering that the availability of a technology in a company is not a sufficient condition for the firm to be able to extract its payoffs, either for the individual or for the firm, but it rather requires the ability to use the technology for production. This may be more important in digital than less digital intensive sectors, if the more advanced technology in digital intensive sectors is more complex to embed in production. Especially in digital intensive industries, the production process might be more decentralised (as e.g. outsourcing, offshoring and vertical integration may occur more frequently) and the bundling of self-organisation and management and communication with advanced numeracy skills is key to ensure the functioning of production and the workflow within teams.

**Table 3. Skills complementary to ICT skills in digital vs. less digital intensive industries**

| | (1) | (2) |
|---|---|---|
| | Workers in Less digital intensive Industries | Workers in Digital intensive Industries |
| (ICT Skills)X(Management and Communication Skills) | 0.002 | 0.009 |
| | (0.005) | (0.006) |
| (ICT Skills)X(Accountancy and Selling Skills) | -0.007 | 0.007 |
| | (0.005) | (0.004) |
| (ICT Skills)X(Advanced Numeracy Skills) | -0.005 | 0.006 |
| | (0.005) | (0.006) |
| (ICT Skills)X(Self-Organisation Skills) | -0.003 | 0.008* |
| | (0.004) | (0.005) |
| (ICT Skills)X(Readiness to Learn) | -0.012*** | -0.017*** |
| | (0.004) | (0.005) |
| (ICT Skills)X(Literacy) | -0.009 | 0.008 |
| | (0.007) | (0.009) |
| (ICT Skills)X(Numeracy) | 0.001 | 0.002 |
| | (0.007) | (0.008) |
| ICT Skills | 0.088*** | 0.091*** |
| | (0.008) | (0.006) |
| Management and Communication Skills | 0.043*** | 0.040*** |
| | (0.004) | (0.006) |
| Accountancy and Selling Skills | -0.029*** | -0.026*** |
| | (0.005) | (0.005) |
| Advanced Numeracy Skills | 0.016*** | 0.020*** |
| | (0.004) | (0.007) |
| Self-Organisation Skills | 0.018*** | 0.039*** |
| | (0.003) | (0.004) |
| Readiness to Learn | -0.009** | -0.008* |
| | (0.004) | (0.005) |
| Literacy | 0.002 | 0.008 |
| | (0.007) | (0.007) |
| Numeracy | 0.038*** | 0.053*** |
| | (0.008) | (0.009) |
| Control Variables | Yes | Yes |
| Observations | 53 770 | 50 526 |
| Adjusted R-squared | 0.570 | 0.585 |

*Note*: The dependent variable is the log of hourly wages. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specification in column 1 is estimated for the sample of individuals working in less digital intensive industries, whereas the specification in column 2 is estimated for the sample of workers in digital intensive industries. The specifications are estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).
*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table 4. Skills complementary to advanced numeracy skills in digital vs. less digital intensive industries**

| | (1) | (2) |
|---|---|---|
| | Workers in Less digital intensive Industries | Workers in Digital intensive Industries |
| (Advanced Numeracy Skills)X(ICT Skills) | -0.009 | 0.001 |
| | (0.006) | (0.007) |
| (Advanced Numeracy Skills)X(Management and Communication Skills) | 0.006 | 0.015*** |
| | (0.005) | (0.003) |
| (Advanced Numeracy Skills)X(Accountancy and Selling Skills) | -0.003 | 0.003 |
| | (0.005) | (0.004) |
| (Advanced Numeracy Skills)X(Self-Organisation Skills) | 0.002 | 0.010** |
| | (0.004) | (0.004) |
| (Advanced Numeracy Skills)X(Readiness to Learn) | -0.010** | -0.016*** |
| | (0.004) | (0.004) |
| (Advanced Numeracy Skills)X(Literacy) | -0.006 | 0.010 |
| | (0.006) | (0.008) |
| (Advanced Numeracy Skills)X(Numeracy) | -0.000 | 0.001 |
| | (0.007) | (0.007) |
| ICT Skills | 0.088*** | 0.091*** |
| | (0.008) | (0.006) |
| Management and Communication Skills | 0.043*** | 0.041*** |
| | (0.004) | (0.005) |
| Accountancy and Selling Skills | -0.028*** | -0.024*** |
| | (0.005) | (0.005) |
| Advanced Numeracy Skills | 0.017*** | 0.016** |
| | (0.004) | (0.007) |
| Self-Organisation Skills | 0.019*** | 0.040*** |
| | (0.003) | (0.004) |
| Readiness to Learn | -0.006* | -0.010** |
| | (0.004) | (0.005) |
| Literacy | 0.002 | 0.009 |
| | (0.007) | (0.007) |
| Numeracy | 0.039*** | 0.053*** |
| | (0.008) | (0.008) |
| Control Variables | Yes | Yes |
| Observations | 53 770 | 50 526 |
| Adjusted R-squared | 0.569 | 0.585 |

*Note*: The dependent variable is the log of hourly wages. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specification in column 1 is estimated for the sample of individuals working in less digital intensive industries, whereas the specification in column 2 is estimated for the sample of workers in digital intensive industries. The specifications are estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

*Source*: Add the source here. If you do not need a source, please delete this line.

**Table 5. Skills complementary to Numeracy skills in digital vs. less digital intensive industries**

| | (1) | (2) |
|---|---|---|
| | Workers in Less digital intensive Industries | Workers in Digital intensive Industries |
| (Numeracy)X(ICT Skills) | -0.005 | 0.001 |
| | (0.005) | (0.005) |
| (Numeracy)X(Management and Communication Skills) | 0.006 | 0.014*** |
| | (0.005) | (0.005) |
| (Numeracy)X(Accountancy and Selling Skills) | 0.008 | 0.002 |
| | (0.005) | (0.004) |
| (Numeracy)X(Advanced Numeracy Skills) | -0.005 | 0.006 |
| | (0.004) | (0.004) |
| (Numeracy)X(Self-Organisation Skills) | -0.007 | 0.007 |
| | (0.005) | (0.005) |
| (Numeracy)X(Readiness to Learn) | -0.004 | -0.011* |
| | (0.004) | (0.005) |
| (Numeracy)X(Literacy) | -0.006 | -0.002 |
| | (0.004) | (0.004) |
| ICT Skills | 0.089*** | 0.089*** |
| | (0.008) | (0.006) |
| Management and Communication Skills | 0.044*** | 0.041*** |
| | (0.004) | (0.005) |
| Accountancy and Selling Skills | -0.028*** | -0.025*** |
| | (0.005) | (0.004) |
| Advanced Numeracy Skills | 0.014*** | 0.023*** |
| | (0.004) | (0.005) |
| Self-Organisation Skills | 0.017*** | 0.039*** |
| | (0.003) | (0.004) |
| Readiness to Learn | -0.005 | -0.009* |
| | (0.004) | (0.005) |
| Literacy | 0.001 | 0.010 |
| | (0.007) | (0.007) |
| Numeracy | 0.037*** | 0.051*** |
| | (0.007) | (0.009) |
| | | |
| Control Variables | Yes | Yes |
| Observations | 53 770 | 50 526 |
| Adjusted R-squared | 0.569 | 0.585 |

*Note*: The dependent variable is the log of hourly wages. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specification in column 1 is estimated for the sample of individuals working in less digital intensive industries, whereas the specification in column 2 is estimated for the sample of workers in digital intensive industries. The specifications are estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

Source: Authors' own compilation on data from PIAAC and other sources.

## Conclusions

The present study investigates how different types of skills, i.e. cognitive as well as non-cognitive skills and personality traits, are rewarded by labour markets. It further assesses whether returns to skills differ between industries that are more digitally intensive, as compared to those that have undergone the digital transformation to a lesser extent. The paper also addresses the important question of skill complementarities and investigates whether and to what extent cognitive and non-cognitive skills are demanded together and if complementarities differ in digital as opposed to less digital intensive industries.

The findings indicate that cognitive as well as non-cognitive skills are strongly rewarded by labour markets, even when controlling for industry and occupation fixed effects, individual control variables (including education) and firm size. In addition, the fact that the returns to task-based skills are still in the same ballpark than those for cognitive skills highlights the importance of task-specific human capital for production and labour markets. Wage returns to ICT skills are twice as large as those to numeracy skills, whereas management and communication skills are almost equally rewarded as numeracy skills.

Furthermore, the results show that digital intensive industries reward workers having relatively higher levels of self-organisation and advanced numeracy skills more than less digital intensive industries. Moreover, for workers in digital intensive industries, bundles of skills are particularly important: workers endowed with a high level of numeracy skills receive an additional wage premium, if they also show high levels of self-organisation or managing and communication skills. Thus, the present analysis contributes to inform policy makers on the relationship between the digital transformation and skills' needs and supply. This is essential for the design of effective and forward-looking skills and employment policies, aimed at aligning labour market demand and supply and at fostering productivity.

Understanding which skills, cognitive as well as non-cognitive, yield high returns in the labour market is also important to address inequality issues and to foster employment and well-being. If the demand of certain skills and certain bundles of skills outgrow the supply for such skills, the rewards of these skills would increase while those for other skills would decline. This skill shortage could easily lead to rising wage inequality and even to a surge of unemployment of workers not possessing these types of skills. For this reason, to curb the rising wage inequality, it may be important to design or target training programs so that they better prepare workers for the specific skills being high in demand, given the acceleration of the digital transformation across occupations and industries. Moreover, the earlier the training takes place, the lower the costs of trainings for cognitive as well as non-cognitive skills become (Cunha and Heckman, 2007; Cunha et al., 2010). Therefore, recognising major skills needed for digitalisation is important not only for labour market policy interventions, but also for policies specifically targeting the education sector.

Finally, as the digital transformation will soon also affect industries that are at present less digitalised, governments will more and more need to equip their populations with a wide range of skills, and to continue doing so over time. This might entail not only strengthening quantitative or cognitive skills, but also combining these with a good endowment of non-cognitive and socio-emotional skills. The proposed work can therefore help countries identifying the sets of key skills their citizens need to be equipped with to succeed in the digital era. This is important for the design and implementation of education and training programmes, as well as to enhance labour market participation and workers' performance.

# *APPENDIX*

**Table A1: Coefficients for the control variables in Table 2**

| | |
|---|---|
| Age | 0.039*** |
| | (0.003) |
| Age squared | -0.000*** |
| | (0.000) |
| Years of education | 0.024*** |
| | (0.003) |
| Gender (male=='1,' female==0)) | 0.124*** |
| | (0.012) |
| Dummy variable for working in a medium size firm (51-250 employees) | 0.069*** |
| | (0.007) |
| Dummy variable for working in a big firm (>250 employees) | 0.154*** |
| | (0.012) |
| Dummy variable for good state of health of the worker | 0.057*** |
| | (0.016) |
| Dummy variable for very good state of health of the worker | 0.077*** |
| | (0.015) |
| Dummy variable for working part time (<='20' hours per week) | 0.067*** |
| | (0.019) |
| Dummy variable for working in a Digital intensive Industry | 0.040*** |
| | (0.010) |
| Interaction terms of digital industry dummy and skill variables | Yes |
| Skill variables | Yes |
| Industry FE (18 industries) | Yes |
| Occupation FE (1 digit isco08) | Yes |
| Country FE | Yes |
| Observations | 104 296 |
| Adjusted R-squared | 0.576 |

*Note*: The dependent variables is the log of hourly wages. In addition to the shown covariates, the specification also includes all skill variables and their interactions with the dummy variable for working in a digital intensive industry as well as fixed effects for the country, industry and occupation the individual works in. The specifications are estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table A2. Robustness for Table 2 (including only one interaction of skills and the digital industry dummy at a time)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Each specification interacts one column skill variable with the dummy variable for Digital intensive Industry | ICT | Management and Communication Skills | Accountancy and Selling | Advanced Numeracy | Self-Organis. | Readiness to Learn | Literacy | Numeracy | Problem Solving |
| Interaction of Digital Industry Dummy and the column skill | 0.023*** | 0.018*** | 0.017** | 0.027*** | 0.023*** | 0.008* | 0.017** | 0.020** | 0.018** |
| | (0.008) | (0.006) | (0.007) | (0.005) | (0.005) | (0.004) | (0.008) | (0.008) | (0.008) |
| Dummy variable for working in a Digital Industry | 0.037*** | 0.037*** | 0.038*** | 0.041*** | 0.038*** | 0.039*** | 0.038*** | 0.039*** | 0.039*** |
| | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) | (0.009) | (0.010) | (0.010) | (0.009) |
| ICT Skills | 0.077*** | 0.088*** | 0.088*** | 0.088*** | 0.088*** | 0.088*** | 0.087*** | 0.087*** | 0.077*** |
| | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.005) |
| Management and Communication Skills | 0.043*** | 0.034*** | 0.041*** | 0.042*** | 0.042*** | 0.042*** | 0.042*** | 0.042*** | 0.040*** |
| | (0.004) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Accountancy and Selling Skills | -0.026*** | -0.027*** | -0.036*** | -0.026*** | -0.026*** | -0.027*** | -0.026*** | -0.026*** | -0.025*** |
| | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Advanced Numeracy Skills | 0.019*** | 0.019*** | 0.019*** | 0.006 | 0.019*** | 0.019*** | 0.019*** | 0.019*** | 0.020*** |
| | (0.003) | (0.003) | (0.003) | (0.005) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Self-Organisation Skills | 0.028*** | 0.029*** | 0.029*** | 0.028*** | 0.018*** | 0.029*** | 0.029*** | 0.029*** | 0.030*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) |
| Readiness to Learn | -0.007* | -0.007* | -0.007* | -0.007* | -0.007* | -0.011** | -0.007* | -0.007* | -0.013*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Literacy | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | -0.002 | 0.006 | 0.012** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) |
| Numeracy | 0.046*** | 0.046*** | 0.046*** | 0.046*** | 0.046*** | 0.046*** | 0.046*** | 0.036*** | 0.038*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.007) |
| Problem Solving | | | | | | | | | -0.002 |
| | | | | | | | | | (0.009) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 104 296 | 104 296 | 104 296 | 104 296 | 104 296 | 104 296 | 104 296 | 104 296 | 77 903 |
| Adjusted R-squared | 0.575 | 0.575 | 0.575 | 0.575 | 0.575 | 0.575 | 0.575 | 0.575 | 0.587 |

*Note*: The dependent variables are the log of hourly wages. In difference to Table 2, the interaction terms of each skill variable with the dummy variable for working in a digital intensive industry enter each specification one at a time (see columns), and not jointly as in Table 2. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specification is estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1)

*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table A3: Robustness checks for Table 2.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Baseline (from Table 1) | Alternative definition of digital intensive industries | Including combined country-(aggregated) industry FE | Including fixed effects for 2 digit isco08 occupation categories | Excluding occupation FE | Excluding industry FE |
| (Digital Sector) X (ICT Skills) | 0.002 | -0.001 | 0.005 | -0.001 | 0.000 | 0.013 |
| | (0.010) | (0.010) | (0.008) | (0.010) | (0.009) | (0.010) |
| (Digital Sector) X (Management and Communication Skills) | 0.002 | 0.000 | 0.001 | 0.007 | 0.007 | 0.004 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| (Digital Sector) X (Accountancy and Selling Skills) | 0.004 | 0.002 | 0.002 | -0.000 | -0.000 | 0.006 |
| | (0.006) | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) |
| (Digital Sector) X (Advanced Numeracy Skills) | 0.018*** | 0.019*** | 0.018*** | 0.017*** | 0.019*** | 0.010* |
| | (0.006) | (0.007) | (0.005) | (0.005) | (0.006) | (0.006) |
| (Digital Sector) X (Self-Organisation Skills) | 0.015*** | 0.023*** | 0.018*** | 0.014*** | 0.023*** | 0.009* |
| | (0.005) | (0.006) | (0.004) | (0.005) | (0.005) | (0.005) |
| (Digital Sector) X (Readiness to Learn) | -0.004 | -0.012** | -0.007* | -0.004 | -0.003 | -0.002 |
| | (0.004) | (0.006) | (0.004) | (0.004) | (0.005) | (0.004) |
| (Digital Sector) X (Literacy) | -0.001 | -0.004 | 0.006 | -0.001 | -0.002 | 0.007 |
| | (0.007) | (0.008) | (0.008) | (0.007) | (0.008) | (0.007) |
| (Digital Sector) X (Numeracy) | 0.011 | 0.018** | 0.009 | 0.011 | 0.013 | 0.003 |
| | (0.008) | (0.007) | (0.007) | (0.008) | (0.008) | (0.008) |
| Digital Sector Dummy | 0.040*** | 0.013 | 0.033*** | 0.050*** | 0.023** | 0.014 |
| | (0.010) | (0.010) | (0.009) | (0.009) | (0.010) | (0.008) |
| ICT Skills | 0.087*** | 0.091*** | 0.086*** | 0.090*** | 0.106*** | 0.086*** |
| | (0.009) | (0.008) | (0.007) | (0.009) | (0.008) | (0.009) |
| Management and Communication Skills | 0.041*** | 0.041*** | 0.042*** | 0.039*** | 0.057*** | 0.038*** |
| | (0.005) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Accountancy and Selling Skills | -0.027*** | -0.025*** | -0.028*** | -0.024*** | -0.037*** | -0.029*** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) |
| Advanced Numeracy Skills | 0.010** | 0.012*** | 0.009** | 0.008** | 0.020*** | 0.018*** |
| | (0.004) | (0.003) | (0.004) | (0.004) | (0.005) | (0.004) |
| Self-Organisation Skills | 0.021*** | 0.022*** | 0.019*** | 0.023*** | 0.023*** | 0.024*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) |
| Readiness to Learn | -0.005 | -0.004 | -0.004 | -0.004 | -0.005 | -0.007 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.004) |
| Literacy | 0.007 | 0.007 | 0.003 | 0.007 | 0.008 | 0.002 |
| | (0.006) | (0.007) | (0.006) | (0.006) | (0.007) | (0.007) |
| Numeracy | 0.041*** | 0.041*** | 0.039*** | 0.041*** | 0.046*** | 0.048*** |
| | (0.009) | (0.009) | (0.008) | (0.009) | (0.009) | (0.009) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Industry FE (18 industries) | Yes | Yes | No | Yes | Yes | No |
| Occupation FE (1 digit Isco08) | Yes | Yes | Yes | No | No | Yes |
| Occupation FE (2 digit Isco08) | No | No | No | Yes | No | No |
| Country FE | Yes | Yes | No | Yes | Yes | Yes |
| (Country) X (Industry) FE | No | No | Yes | No | No | No |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 104,296 | 104,296 | 104,296 | 104,040 | 104,296 | 104,296 |
| Adjusted R-squared | 0.576 | 0.575 | 0.586 | 0.577 | 0.564 | 0.568 |

*Note*: The dependent variables are the log of hourly wages. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. Column 1 shows the baseline specification from Table 2. The specification in column 2 defines digital intensive industries as the top quartile instead of the top 50% industries regarding the digitalisation index. Column 3 additionally includes combined country-18 aggregated sector FE, whereas column 4 includes fixed effects for 2 digit isco08 occupation categories instead as for one digit occupation categories. Column 5 excludes occupation FE and column 6 industry FE from the baseline specification in column 1. The specifications are estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardized to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table A4. Alternative specifications for Table 3 (including only one interaction of ICT skills and other skills at a time)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Each specification interacts ICT Skills with one column skill variable | Management and Communication Skills | Accountancy and Selling | Advanced Numeracy | Self-Organisation | Readiness to Learn | Literacy | Numeracy | Problem Solving |
| Dependent Variable is log of hourly wages | | | | | | | | |
| Panel A: Less digital intensive Industries | | | | | | | | |
| Interaction of ICT Skills and the column skill | -0.007 | -0.011** | -0.012** | -0.007 | -0.015*** | -0.011* | -0.009 | -0.016*** |
| | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.005) |
| Observations | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 38 920 |
| Adjusted R-squared | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.582 |
| Panel B: Digital intensive Industries | | | | | | | | |
| Interaction of ICT Skills and the column skill | 0.011* | 0.011** | 0.011* | 0.009* | -0.011** | 0.010* | 0.009* | -0.004 |
| | (0.006) | (0.005) | (0.007) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) |
| Observations | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 38 983 |
| Adjusted R-squared | 0.584 | 0.584 | 0.584 | 0.584 | 0.584 | 0.584 | 0.584 | 0.597 |

*Note*: The dependent variable is the log of hourly wages. In difference to Table 3, the interaction terms of each skill variable with ICT skills enter each specification one at a time (see columns), and not jointly as in Table 3. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specifications in Panel A are estimated for the sample of individuals working in less digital intensive industries, whereas the specifications in Panel B are estimated for the sample of workers in digital intensive industries. The specification is estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardised to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table A5. Alternative specifications for Table 4 (including only one interaction of advanced numeracy skills and other skills at a time)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Each specification interacts Advanced Numeracy Skills with one column skill variable | ICT Skills | Management and Communication Skills | Accountancy and Selling | Self-Organis. | Readiness to Learn | Literacy | Numeracy | Problem Solving |
| Dependent Variable is log of hourly wages | | | | | | | | |
| Panel A: Less digital intensive Industries | | | | | | | | |
| Interaction of Advanced Numeracy Skills and the column skill | -0.012** | -0.001 | -0.006 | -0.002 | -0.011*** | -0.009* | -0.008 | -0.008** |
| | (0.005) | (0.004) | (0.004) | (0.005) | (0.003) | (0.004) | (0.005) | (0.004) |
| Observations | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 38 920 |
| Adjusted R-squared | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.582 |
| Panel B: Digital intensive Industries | | | | | | | | |
| Interaction of Advanced Numeracy Skills and the column skill | 0.011* | 0.016*** | 0.009** | 0.012*** | -0.008* | 0.011** | 0.010** | 0.004 |
| | (0.007) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.004) | (0.004) |
| Observations | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 38 983 |
| Adjusted R-squared | 0.585 | 0.584 | 0.585 | 0.584 | 0.584 | 0.584 | 0.584 | 0.584 |

*Note*: The dependent variable is the log of hourly wages. In difference to Table 4, the interaction terms of each skill variable with Advanced numeracy skills enter each specification one at a time (see columns), and not jointly as in Table 4. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specifications in Panel A are estimated for the sample of individuals working in less digital intensive industries, whereas the specifications in Panel B are estimated for the sample of workers in digital intensive industries. The specification is estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardized to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1).

*Source*: Authors' own compilation on data from PIAAC and other sources.

**Table A6. Alternative specifications for Table 5 (including only one interaction of Numeracy and the other skills at a time)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Each specification interacts Numeracy with one column skill variable | ICT | Management and Communication Skills | Accountancy and Selling | Advanced Numeracy | Self-Organis. | Readiness to Learn | Literacy | Problem Solving |
| | Dependent Variable is log of hourly wages | | | | | | | |
| | Panel A: Less digital intensive Industries | | | | | | | |
| Interaction of Numeracy and the column skill | -0.009 | -0.002 | 0.000 | -0.008 | -0.009 | -0.007 | -0.008* | -0.012*** |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) | (0.004) | (0.004) |
| Observations | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 53 770 | 38 920 |
| Adjusted R-squared | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.569 | 0.582 |
| | Panel B: Digital intensive Industries | | | | | | | |
| Interaction of Numeracy and the column skill | 0.009* | 0.016*** | 0.010** | 0.010** | 0.010 | -0.003 | 0.002 | -0.000 |
| | (0.005) | (0.003) | (0.004) | (0.004) | (0.006) | (0.006) | (0.005) | (0.005) |
| Observations | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 50 526 | 38 983 |
| Adjusted R-squared | 0.584 | 0.585 | 0.584 | 0.584 | 0.584 | 0.584 | 0.584 | 0.597 |

*Note*: The dependent variables is the log of hourly wages. In difference to Table 5, the interaction terms of each skill variable with numeracy skills enter each specification one at a time (see columns), and not jointly as in Table 5. In addition to the shown covariates, the specifications also include age, age squared, years of education, gender, two dummy variables for the size of the firm the individual works, a dummy variable for whether the individual works less than 21 hours a week, two dummy variables for the state of health of the individual as well as fixed effects for the country, industry and occupation the individual works in. The specifications in Panel A are estimated for the sample of individuals working in less digital intensive industries, whereas the specifications in Panel B are estimated for the sample of workers in digital intensive industries. The specification is estimated by weighted OLS using individual senate weights to give each country the same weight in the regression, while robust standard errors are clustered at the country level. All skill variables are standardized to mean zero and variance of one for the pooled sample using senate weights to weight observations from single countries. (*** p<0.01, ** p<0.05, * p<0.1)

Source: Authors' own compilation on data from PIAAC and other sources.

# Endnotes

[1] Also in the literature on the effects of offshoring on wages and employment, the evidence strongly points to the importance of task-specificity of human capital compared to occupation or industry specificity (Baumgarten et al. 2013).

[2] The effect of technological change on the decrease of employment in occupations associated with a high share of routine tasks and labour market polarisation has been document by a wealth of empirical studies including Acemoglu (1998); Autor, Levy and Murnane (2003); Autor (2015) and Acemoglu and Restrepo (2016).

[3] The research on personality traits (or non-cognitive skills), especially for North America, has been organised following the so-called "Big Five" factor model of personality (Goldberg, 1990). This suggests that most personality measures could be subsumed under an umbrella including five key factors: extraversion, agreeableness, conscientiousness (or dependability), emotional stability (vs. neuroticism), and openness to experience.

[4] Digital intensive sectors are: wood and paper products, and printing (ISIC Revision 4 sectors 16 to 18), computer, electronic and optical products (26), electrical equipment (27), machinery and equipment n.e.c. (28), transport equipment (29-30), furniture, other manufacturing and repair and installation of machinery and equipment (31-33), wholesale and retail trade, repair of motor vehicles and motorcycles (45-47), publishing, and broadcasting activities (58-60), telecommunications (61), IT and other information services (62), financial and insurance activities (64-66), legal and accounting activities (69-71), scientific research and development (72), advertising and market research, other professional, scientific and technical activities (73-75), administrative and support service activities (77-82), public administration and defence, compulsory social security (84), arts, entertainment and recreation (90-93), other service activities (94). The taxonomy of sectors exploited here relies on information for 2011-2012 only, so as to match the period covered by the early round of the PIAAC survey. Being constructed ad hoc for the current analysis the taxonomy may not correspond perfectly to the classification in Calvino et al. (2018). Only countries for which all indicators are found to be non-missing for all industries are considered for the purpose. These include: Australia, Austria, Denmark, Finland, France, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom, the United States. For more information on the taxonomy, see Calvino et al. (2018).

[5] Note that the labels for two of the indicators in Grundke et al. (2017a) have changed. “STEM-quantitative skills” are now labelled “Advanced Numeracy skills” and “Marketing and Accounting skills” are called “Accountancy and Selling skills”.

[6] A specification using problem solving in technology rich environments, too, is reported as robustness check. Problem solving is not available for France, Italy and Spain (as these countries did not participate in the test, the sample would decrease by almost 30000 observations) and suffers from non-response problems of generally less skilled individuals in the other countries which would lead to a selection bias in our estimation (OECD 2016). As a consequence, problem solving in technology-rich environment is not included in the baseline specification.

[7] The higher level of technology adoption in digital intensive sectors can make individuals more productive for each level of skill endowment, and this productivity is rewarded in the form of salaries (e.g. to motivate workers). Firms in digital intensive sectors may also invest more in their internal organisation, so as to react flexibly to changes in the production environment, and may therefore be better at matching workers

with the job tasks that suit them the best. They may also be better at monitoring workers thanks to the technology embedded in production.

[8] In a second specification, the dependent variable log of the monthly wage is used and results do not change. Results can be obtained from the authors upon request.

[9] In robustness checks, a digital industry is defined as an industry with a higher digital intensity than the 75th percentile for all 36 considered industries and results do not change (Table A3).

[10] Following Wiederhold (2016) Hanushek et al. (2015), this paper uses the first value of numeracy and literacy for each individual in the estimation. Results using the repost command and all 10 values per individual are very similar to using only the first value and are available upon request.

[11] The size classes are so-defined in the PIAAC dataset itself.

[12] These 18 industries are aggregates of the 34 industries used in the OECD TiVA database, and include two resource extraction sectors, nine manufacturing sectors and seven services sectors.

[13] In robustness checks, combined fixed effects for countries and 18 aggregated industries (TiVA 18) are included and results do not change (col. 3 in Table A3). We also include fixed effects for 2 digit isco08 occupation categories and results do not change (col. 4 in Table A3).

[14] A first type of endogeneity concerns shocks which may simultaneously increase wages and affect whether a sector becomes digital or less digital intensive. A second type of endogeneity stems from the self-selection of workers into tasks for which they have a comparative advantage, as in Roy (1951), Firpo et al. (2011) or Acemoglu and Autor (2011), which is likely to bias the coefficient of the return to task-based skills upwards.

[15] The full list of controls in the baseline regression includes: a worker’s age and age squared (to account for non-linearities), years of education, health, gender, the worker being on part time, and a control for the size of the firm in which the worker is employed. Results are robust to including the education of a worker’s parent as a further control, although doing so reduces sample size by more than 5000 observations - which is why this variable is excluded from the baseline specification. The estimated coefficients for the control variables can be found in Table A1.

[16] Another test estimates the same specification but based on monthly rather than hourly wages. Results do not change qualitatively and are available on request.

[17] In column 4 of Table A3, we also include fixed effects for 2 digit isco08 occupation categories and results do not change.

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