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Skills and global value
chains: A characterisation

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SKILLS AND GLOBAL VALUE CHAINS: A CHARACTERISATION

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ABSTRACT

Empirical studies have traditionally measured workers' skills by educational attainment or occupational status. Recent literature using country-specific information on the task content of jobs to identify the different skills of individuals argues that neither these proxies measure skills adequately, as large wage heterogeneity still exists within education and occupation classes. This study follows a job task-based approach and exploits the rich information contained in the OECD Survey of Adult Skills (PIAAC) to conduct an exploratory state-of-the-art factor analysis. The six task-based skills indicators thus extracted have the characteristic of being comparable across 31 countries and allow clearer interpretation than indicators proposed by previous literature. Moreover, by combining the PIAAC-based skills indicators with data from the OECD Trade in Value Added (TiVA) database, light is shed on the way different skills and their distributions (at the country-industry level) relate to industry performance and to integration into global value chains (GVCs). The results underline the importance of cognitive skills such as literacy, numeracy and problem solving for any industry to thrive in the global economy. Also, a persistent and positive association with labour productivity and participation in GVCs is observed, at the industry level, for non-cognitive skills such as managing and communication skills, ICT skills and workers' readiness to learn and to think creatively.

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EXECUTIVE SUMMARY

The paper is the result of joint work between the OECD Directorate for Science, Technology and Innovation (STI) and the OECD Directorate for Education and Skills (EDU).

It develops new indicators of cognitive and non-cognitive skills that matter for performance on the job and for firm performance. It characterises the cross-country distribution of these skills by occupation, age, gender, as well as by industry and firm size. An industry-level analysis of the relationships existing between the skills composition of the workforce, economic performance and the generation of value added from trade is also undertaken.

This work is motivated by the fact that while existing studies agree on the importance of skills for trade patterns, they seldom specify which skills matter for economic performance and for participation in global value chain (GVCs). Also, designing effective industry, education and trade policies requires relying on more accurate measures of skills, which go beyond those usually considered and that are usually based on educational attainment or occupational status.

This work combines information from the OECD Survey of Adult Skills (PIAAC) and the OECD Trade in Value Added (TiVA 2015) database. Skills are measured in two ways. On the one hand, information on three assessed cognitive skills (numeracy, literacy and problem solving in technology rich environments) from PIAAC is used. On the other hand, it relies on skills indicators built on the basis of exploratory factor analysis using information on the frequency of tasks performed on the job and on other self-reported individual characteristics. These cognitive and non-cognitive skill measures are combined with indicators of economic performance and participation in GVCs (namely: labour productivity, exports in gross and value added terms, forward and backward linkages¹) to investigate the skill-GVC nexus.

A number of policy relevant findings emerge from the analysis:

- Skills distributions are generally very heterogeneous across all dimensions considered, including country, industry and occupation and to a lesser extent firm size.
- *Cognitive skills play a major role across any industry.* The three cognitive skills considered in the analysis, i.e. *literacy, numeracy and problem solving*, appear to be a general, industry- and task-independent set of skills that positively relate to labour productivity and to integration into GVCs in all industries. This is true irrespective of the idiosyncratic characteristics of each industry. Thus, the education system plays a major role in ensuring that workers are endowed with those 3 cognitive skills early in life, which in turn may increase productivity and greater forward integration of industries into GVCs.
- *The correlation between task-based skills, performance and participation in GVCs is more industry-specific.* In contrast to cognitive skills, *task-based skills* exhibit more industry specific and generally relatively weaker relationships with productivity and international forward integration. However, among the task-based skills considered, *ICT skills, Management and Communication skills* and *Readiness to Learn* are significantly and positively associated with productivity and with forward integration into GVCs, for all industries.

- Increasing productivity and forward integration into GVCs calls for industries to specialise in specific tasks. This in turn requires having a workforce endowed with the skills needed to carry out those tasks. The latter may represent an important challenge for countries and for the design of policies aimed to promote the structural transformation of economies. *Enhanced coordination and alignment of industrial and trade policies with education and skills policies seems thus necessary to avoid counteracting policies and possible inefficiencies.*
- *Skills at the highest end of the industry-level distribution matter the most.* Analysis of the industry-level distribution underlying the mean values observed for all types of skills shows that results are mainly driven by the 90th percentile of the industry-level skill distribution. This in turn suggests that having a (relatively small) group of highly skilled people is important for productivity and integration of industries into GVCs. Whether this depends on the existence of e.g. frontier firms or other determinants remains a question for future research, as firm-level data enabling this type of analysis are not available at present.
- *Cognitive skills* are also significantly and positively associated with backward integration of industries in GVCs, although the association is much weaker in the case of foreign value added embedded in domestic final demand than the one in exports. Moreover, higher imports of intermediate inputs (i.e. backward linkages) that are not linked to domestic exporting activities are associated with lower industries needs in terms of *ICT, STEM-quantitative* and *Marketing and Accounting skills*, irrespective of the idiosyncratic characteristics of each industry.
- *With participation in global value chains, the skills of workers in the services sector deserve greater attention.* The analysis also suggests that, in order to investigate the effects of policies on the international integration of industries into GVCs, it is crucial to account for the fact that services sectors export a much higher share of their value added through indirect links than through direct ones. Hence, policies aiming to provide workers with the skills needed for the internationalisation of economies should also focus on the skills requirements of the services sectors, traditionally labelled as “non-tradable sectors”, as services are often important suppliers of intermediate inputs to the directly exporting manufacturing industries.

SKILLS AND GLOBAL VALUE CHAINS: A CHARACTERISATION

Introduction

Background and motivation

In 2014 the Working Party on Industry Analysis (WPIA) scoped for the Committee on Industry, Innovation and Entrepreneurship (CIIE) a horizontal project capitalising on existing work on Knowledge Based Capital (KBC), TiVA and Global Value Chains (GVCs). The aim of this project was to broaden the scope of the existing GVCs (OECD, 2013a) and KBC (OECD, 2013b) analyses to encompass the skills and employment dimensions. The focus was on the complex interactions that exist between investment in KBC, workforce skills, employment, and participation and positioning in global value chains, both at the industry and economy levels.

The project consisted of three main lines of work, each articulated over several policy-relevant questions, some of which jointly carried out with the Directorate for Employment, Labour and Social Affairs (ELS), the Trade and Agriculture Directorate (TAD) and the Directorate for Education and Skills (EDU).

This paper is based on joint work with EDU and aims at characterising the distribution of skills across countries, industries and occupations, and at investigating the relationship existing between the skills composition of the workforce, and the generation of value added from trade. Identifying the skills that affect participation in GVCs is an important step in assessing how policies, such as those related to education, training and work organisation, as well as industrial policy aimed at enhancing productivity and growth can help countries capture value from trade. More precisely, this paper addresses research questions such as:

- i) What are the skills that are more relevant for performance on the job and for firm performance?
- ii) How are these skills distributed across firms, industries and economies as well as by individual characteristics such as age and gender?
- iii) How does the skill endowment of the workforce and the frequency of different tasks performed on the job relate to activities performed within GVCs?

To address these questions, work detailed in Grundke et al. (2016a) carries out an extensive literature review aimed at informing the construction of a normative taxonomy of skills that are found to be relevant for performance on the job and for firm performance.² This normative taxonomy is then operationalised using information from the Survey of Adult Skills (PIAAC) about assessed cognitive skills, the frequency of tasks performed on the job as well as about other self-reported individual characteristics. The allocation of survey items to skill-related indicators, based on the literature review and on abstract reasoning, leads to the construction of 17 skill indicators, which are further grouped into four broad categories mirroring the continuum of skills that workers can be endowed with. These are: cognitive skills, assessed both through externally administered tests and by means of using information on the tasks performed on the job; skills combining cognitive skills and personality traits, which are mainly inferred using information on the job tasks performed; personality traits; and physical skills, as they emerge from information about the tasks carried out on the workplace.

This normative approach, while leading to the construction of indicators that can be easily interpreted, cannot ensure that the indicators proposed indeed measure inherently different skills. Also it is not clear whether the PIAAC survey items contributing to shape one indicator are ultimately capturing the same underlying latent skill. To address this concern and construct indicators each serving as proxies of different skill sets that are relevant for performance on the job and for firm performance, this study pursues an advanced exploratory factor analysis as proposed by Conti et al. (2014). Such an approach represents a data grounded method aimed to ensure that the PIAAC survey items ultimately contained within one indicator do measure the same underlying type of skill, and that no skill-related indicator exploits the same piece of information (i.e. PIAAC item) informing the construction of another skill proxy.

The exploratory factor analysis proposed relies on 57 PIAAC Survey items, all related to the frequency of the tasks performed on the job and on self-reported individual characteristics. The analysis leads to the construction of six new skill indicators, namely: *information and communication technologies (ICT) skills*; *readiness to learn and creative problem solving*; *managing and communication*; *self-organisation*; *marketing and accounting*; and *science, technology, engineering and mathematics (STEM)–quantitative skills*. Together with the three assessed cognitive skills contained in PIAAC (i.e. numeracy, literacy and problem solving), these six new skill indicators are used to describe the skills distribution of workers across occupations, industries and countries, as well as to analyse the relationship between the different moments of the country-industry distributions of various skills and the performance and integration of industries in GVCs.

In addition to contributing to the 2015-2016 programme of work and budget (PWB) of the CIIE, the analysis presented in this paper is at the core of the OECD Skills Outlook 2017, which has a focus on "Skills and GVCs". The Skills Outlook provides an integrated approach to skills issues based on the multidisciplinary knowledge of the OECD and using the holistic lens of the OECD Skills Strategy. It offers governments and stakeholders in-depth analysis, policy insights and concrete examples from country experience on specific skill-related issues. The 2017 edition aims at better understanding the role of skills and of skills-related policies in the relationships between GVCs and productivity, growth and inequalities. It also aims at characterising countries' needs in terms of skills and skills-related policies to make the most of GVCs.

Some of the indicators generated by this study are further used in analysis investigating the way in which skill bundles shape the comparative advantages of industries and performance in GVCs (see Grundke et al. 2017).

Skills and GVCs

The skill composition of the workforce, the tasks performed on the job and the interaction between skills and tasks are expected to contribute to the performance and competitiveness of firms and industries, and to their positioning in global value chains. Existing empirical evidence supports the predictions of theoretical models and suggests that skill endowments relate positively to the probability of being employed and to job quality, as captured by income levels and prospective career paths, and to the ability of firms to innovate and perform.

How workers apply these skills to the tasks they perform or how they use their skills on the job also contribute to firm performance (Autor, 2013). High-skilled human capital is expected to carry out complex tasks, which should generally lead to better economic performance, e.g. in terms of productivity, either directly or through complementarity with technology (Acemoglu, 2002). While theory and empirical findings suggest the relations between skills and firm performance to hold at the country level, evidence on a cross-country or industry basis remains scarce. The literature on the relationship between skill endowments, tasks performed on the job, and participation and positioning in GVCs at the industry and

economy-wide level is also fairly scant. The lack of empirical evidence in this respect hinders the design of policies aimed to improve participation in GVCs and ‘social upgrading’, intended as the up-skilling of the labour force and improvements in the returns to labour.

As a caveat to the work presented in this paper, it should be noted that, despite generating interesting evidence, the characterisation proposed is to be considered suggestive in nature and exploratory in scope, as we lack a solid theoretical and empirical basis on which to rely. While existing studies agree on the importance of skills (generally proxied by education) for trade patterns, they nevertheless very seldom specify which skill matters for which type of GVC participation or performance-related measure.

In what follows, the paper first gives a short review of the literature on the link between skills, jobs and economic performance. It then presents the explanatory factor analysis carried out to construct the new skill indicators using data from the Survey of Adult Skills (PIAAC). Third, a characterisation of skill endowment and skills as they emerge from the tasks performed on the job is then offered, at the country, industry and occupation level. Fourth, this study provides regression results about the link between industry-level endowment of workforce skills and industries’ performance and participation in global value chains. The relationships between performance indicators and different moments of the country-industry skill distribution are also explored, in terms of both productivity and TiVA indicators.

Setting the scene: the link between skills, jobs and economic performance in the literature

Understanding the links between workers’ skills and capabilities on the one hand and performance on the job and economic performance on the other hand requires a theoretical underpinning. Two frameworks appear particularly relevant in this respect: the Resource Based View (RBV) of the firm and the High-Performance Work Systems (HPWS) approach. In addition, the economics literature focusing on education and skills provides important insights on the role of individuals’ abilities for labour market outcomes.

Thanks to the pioneering work of scholars like James Heckman, individuals’ skills have been recognised as fundamental determinants of economic and social success. In turn, formal academic institutions as well as families and firms have been recognised as sources of learning (Heckman, 2000). Cognitive skills involve conscious intellectual efforts and include long- and short-term memory, auditory processing, visual processing, processing speed, and logic and reasoning. “Non-cognitive skills”, also known as “soft skills” or personality traits or character qualities, involve the intellect in a more indirect and less conscious fashion than cognitive skills, and relate to individuals’ personality, temperament, attitudes, integrity and interpersonal interaction. Examples of studies arguing for the importance of cognitive skills for job performance are Schmidt (2002), Schmidt and Hunter (2004) and Hanushek and Woessmann (2008). Heckman and Rubinstein (2001) emphasise the importance of non-cognitive skills in particular. Finally, many analyses stress the importance of both cognitive and non-cognitive skills for occupational attainment and performance on the job (e.g. Heckman et al., 2006; Kautz et al., 2014).

While an extensive literature survey on the link between skills, jobs and economic performance can be found in Appendix B to the present document³, this paper proposes only a brief overview of the discussion addressing workers’ skills that have been found to be important for performance on the job and for economic performance. Attention is here devoted to the skills that are used for the characterisation and the empirical analysis presented in the paper, i.e. the assessed cognitive skills from PIAAC (numeracy, literacy and problem solving) as well as the new skill indicators emerging from the exploratory factor analysis.⁴

Cognitive skills***Reading, writing and numerical skills***

Broad agreement exists in the fields of industrial organisation, psychology and labour about the fact that general cognitive ability - which is essentially the ability to learn - helps predict both occupational level attained and occupation-related performance, as well as the ability to benefit from training (e.g. Schmidt, 2002, Schmidt and Hunter, 2004). A subset of cognitive abilities called specific aptitudes, or simply aptitudes, include verbal aptitude, spatial aptitude, and numerical aptitude.

Many are the studies emphasising the importance of cognitive skills and, more recently, the joint importance of cognitive and non-cognitive skills (discussed later) for job and economic performance. For instance, Hanushek and Woessmann (2008) argue that there is strong evidence that the cognitive skills of the population, rather than school attainment, relate to individual earnings, the distribution of income and more generally economic growth. Heckman and Vytalacil (2001) however caution that since cognitive ability and schooling are so strongly related it is basically impossible to independently vary these two variables and still be able to estimate their impact separately.

ICT skills

Existing studies in different fields point to the importance of Information and Communication Technologies (ICT) for firm performance, intended as investment in ICT hardware and software as well as ICT related skills. Management and organisation-related analyses in a Resource Based View (RBV) context argue that ICT should be considered as an organisational capability and find that ICT capabilities increase firm performance (Bharadwaj 2000, Santhanam and Hartono 2003, Tippins and Sohi 2003). Economic studies in the field generally find that both computer skills and high-level communication skills endowments are positively associated with higher firm productivity and higher wage premia for workers (Dickerson and Green 2004, MacCrory et al.'s 2015, Bloom et al.'s 2014).

Skills combining aspects of cognitive abilities and personality traits***Managerial and organisational competencies***

More than half a century of psychology, human resources, organisation, management, finance, entrepreneurship, innovation and economics studies have underlined the relevance of different managerial profiles, tasks and abilities for the performance of firms. Among others, these highlight the importance of strategic management abilities for the generation of sustainable competitive advantages (e.g. Hill et al, 2014) and for enhancing competitiveness in global markets (e.g. Hitt et al. 2012). In turn, and given the centrality of human resources for the competitiveness of firms, emphasis is put on the need of suitable human resource management (HRM) practices to effectively align organisational, group and individuals' objectives with organisations' strategies (see e.g. Lazear and Gibbs, 2014; Buller and McEvoy, 2012). Among the key tasks to be accomplished and the skills needed for an effective HRM and for strategic management more generally the literature suggests those related to: activities and workforce planning; advising and instructing staff; influencing decisions; negotiating; solving problems; and communicating (see Armstrong and Taylor, 2014, for an extensive discussion).

Recent cross-country studies further find that management practices differ substantially not only across firms, but also across countries and industries (e.g. Bloom and Van Reenen, 2010; Bloom et al., 2012), thus warning about generalising results obtained in the context of specific industries and countries. Also, OECD efforts aimed to better define and measure organisational capital find that managers are not the sole to perform managerial tasks affecting the long-term functioning of firms such as developing

objectives and strategies, organising, planning, supervising production and managing human resources (Squicciarini and Le Mouel, 2012; Le Mouel and Squicciarini, 2015). Such findings support Caroli and Van Reenen's (2001) and von Krogh et al.'s (2012) argument about the progressive devolution of tasks traditionally carried out by managers to a wider array of non-managerial occupational profiles. This decentralisation of authority and layering of managerial functions in turn suggests that firm-specific managerial skills and abilities should be assessed and compared across a number of occupational profiles, and not only with respect to managers.

Creative problem solving and learning ability

Common sense, theory and evidence all emphasise the importance of problem solving abilities, both individual-specific and group-related ones, as they are conducive to superior individual and organisational performance. The role of problem solving skills and abilities has been investigated in relation to a wide array of policy-relevant issues, including firm performance, creativity, innovation, leadership, management and entrepreneurship. A part of this vast and diversified literature addresses the role played by problem solving in developing organisational capabilities and improving firm performance (Nickerson and Zenger 2004, Katila and Ahuja 2002, Tippman et al. 2013).

The literature addressing the problem solving and creativity link is also very rich, both at the individual and the group level. Problem solving attitude and skills are found to be highly and positively correlated with both individual and "organizational creativity" (Woodman et al., 1993), intended as the creation of a valuable, useful new product, service, idea, procedure, or process by individuals working together in an organisation. Consensus also seems to exist about problem solving abilities being directly and indirectly - i.e. through the creativity conduit - related to innovation, and about problem solving ability and creativity being linked to entrepreneurial endeavours' creation and success. Finally, problem solving and creativity have been analysed in relationship to leadership's traits and needs, and found to be a key component of leadership, also managerial leadership.

Self-organisational ability and flexibility on the job

Evidence about the mechanisms through which high performance work systems lead to superior firm performance find adaptive capabilities and workers' flexibility to be key in this respect (see, e.g. Messersmith and Guthrie, 2010; Wei and Lau, 2010). As the current knowledge-based global economic paradigm calls for an ever greater ability to adapt to change and absorb shocks, systems and actors need to be able to adapt and remain flexible. This poses a number of management challenges and ultimately entails having a broader perspective on human resource management, especially in emergent organisations (Messersmith and Guthrie, 2010).

Identifying cognitive and non-cognitive skills: a factor analysis approach

As mentioned, this study aims to identify and define a narrow set of indicators representing key performance-related skills of the workforce and to investigate how skill patterns vary by country, industry, occupation, firm size, age and gender. To construct these indicators, it performs an advanced exploratory factor analysis using information about the frequency of the tasks performed on the job as well as other self-reported individual characteristics from the OECD Survey of Adult Skills (PIAAC). Doing so, the analysis follows in the steps of recent labour economics literature assessing the different dimensions of skills based on the tasks that workers perform on the job (e.g. Ingram and Neumann 2006; Poletaev and Robinson 2008; Gathman and Schoenberg 2010). Arguing that there is large unobserved skill heterogeneity within education classes and that educational attainment alone does not measure skills adequately, this literature uses survey information on the task contents of jobs to infer the skills possessed by individuals.

More precisely, Ingram and Neumann (2006) and Poletaev and Robinson (2008) use U.S. data on 53 job characteristics from the Dictionary of Occupational Titles (DOT) in the year 1995 and exploratory factor analysis to extract four underlying skill dimensions. Ingram and Neumann (2006) estimate the labour market returns to this four skill dimensions whereas Politaev and Robinson (2008) investigate the extent to which the skills acquired in this four dimensions are specific to or can be transferred across occupations.

While the DOT data rely on information provided by U.S. job specialists (not by the workers themselves) and mainly on binary information on whether or not different jobs feature certain characteristics, the OECD Survey of Adult Skills on which this study relies contains information directly supplied by workers about the frequency with which tasks are carried out. Moreover, data relate to 31 countries and allow for cross-country comparative analysis.⁵ This leads to obtaining skill indicators that are clearer to interpret and sharper to distinguish from those extracted by Ingram and Neumann (2006) and by Poletaev and Robinson (2008), as it will become clear in the analysis that follows.

The 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 65.⁶ Data collection was completed in 2011-12 for the first round (22 OECD countries and Russia, OECD, 2013) and for the second round in 2014-2015 for six OECD countries, plus Singapore and Lithuania (OECD, 2016).⁷ 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.⁸ The database contains information on 208 620 individuals of which 138 605 were employed at the time of the interview.⁹

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. Finally, the Survey gives information on workers' attitude towards learning, trust, health and other issues, which are gathered through self-reported assessments. A number of background characteristics such as educational attainment and job characteristics (ISCO codes and industry codes) complement the information on skills.

Most of the items that this analysis relies upon belong to two sections of the PIAAC background questionnaire: the F section describes the use of skills at work; the G section focuses more specifically on numeracy-, literacy- and ICT-related use of skills. All these items are frequency questions scaled between 1 ("Never") and 5 ("Every day")¹⁰. This set is completed with items on work flexibility, learning strategies, management and trust from section D and I of the background questionnaire. Questions on work flexibility and learning strategies are also scaled between 1 and 5, but they capture the respondent's extent of agreement with a statement, and answers range between 1 ("Not at all") and 5 ("To a very high extent"). The items on management and trust are also scaled between 1 and 5, but measure the number of people supervised (management) and the agreement to a statement on trust, respectively.¹¹ For the construction of the skills indicators, single items were rescaled in a 0-1 interval, with 1 being the highest skill score and 0 the lowest one.¹²

In total, this study relies on 57 items from section D, F, G and I from the PIAAC background questionnaire (Table A2 and A3). The choice of these items relies on a number of criteria. First, for exploratory factor analysis purposes, items need to exhibit a certain degree of consistency. Second, the range of chosen items needs to be diverse enough as to encompass the diversity of skills that workers are

endowed with (Conti et al. 2014). Third, because single item indicators are not meaningful, a given item should not be conceptually isolated from other items contained in the initial set. Facing the trade-off between consistency and the diversity of included items, the analysis finally exploits items related to work flexibility, learning strategies, management and trust, even though those items are not framed as frequencies of use of a given skill.

As a caveat to the analysis that follows and to the one presented in Grundke et al. (2016a), it is worth underlining that, while the OECD Survey of Adult Skills offers a wealth of information, it was not conceived for analyses like the one presented in this work. As the set of items used in this analysis is constrained by the list of items available in this survey, it cannot be excluded that some relevant dimensions might not have been captured (sufficiently well). It is thus important not to consider this taxonomy as exhaustive.

From a normative skills typology to skills indicators based on a statistical analysis

The questions in PIAAC of possible relevance for the analysis, although rich and insightful, are too many to be used as such and need to be summarised by synthetic indicators. In the normative approach initially pursued (Grundke et al., 2016a) the relevant set of skills is identified and items are allocated to the different skill sets based on a literature review and reasoning. This leads to the construction of 17 indicators of skills that could be further grouped into 5 broad categories. The idea is that skills should be seen as a continuum, with some of them being mainly cognitive, others being close to personality traits, and an important group combining the two aspects. Table 1 shows the normative skills typology proposed in Grundke et al. (2016a).

Table 1. Normative typology of performance-relevant skills identified in PIAAC

Cognitive Skills		Literacy
		Numeracy
		Problem-solving in technology-rich environment
Cognitive skills (Using Information on Tasks Performed)	Complex	Reading and writing
		Numerical skills
		ICT skills
	Less complex	Reading and writing
		Numerical skills
		ICT skills
Skills combining cognitive skills and personality traits (Using Information on Tasks Performed)		Problem-solving
		Self-organisational skills
		Interacting and communicating
		Managing
Personality traits		Conscientiousness and job engagement
		Readiness to learn and creative thinking
		Trust in persons
Physical skills (Using Information on Tasks Performed)		Physical skills

Source: Grundke et al. (2016a)

The normative approach leads to the identification of skills indicators that can be easily interpreted. However, it does not ensure that these indicators are statistically relevant in terms of the covariance structure of the questions used in the PIAAC survey. For instance, some items might be allocated to the wrong skills category. Also, those skills indicators that are highly correlated might need to be merged, or others might need to be split if they are found to convey different information.

To address this concern, this work uses the results of an advanced exploratory factor analysis similar to the one described in Conti et al (2014) to define a narrow set of skills indicators. The methodology assumes the existence of a certain number of unobserved latent variables, called factors, whose joined variation explains the correlation pattern of a larger set of observed variables (or items). Each factor is a weighted combination of the observed variables, whereby the weights are called *factor loadings*. It is important to note that the number of factors is a parameter of the model and needs to be chosen carefully using certain criteria established in the literature (Conti et al. 2014; Costello and Osborne 2005). The algorithm underlying the exploratory factor analysis, described in the next section, leads to the extraction of factors that serve as the basis for the creation of the new skills indicators. The technical description that follows can be overlooked by those readers interested in the results of the analysis only.

Main steps of the exploratory factor analysis

One of the main drawbacks of classical exploratory factor analysis is that the observed variables may be associated with all factors. In this case, a factor is a linear combination of all observed variables, with weights on the observed variables that differ and range from -1 to 1. Such types of factors are more difficult to interpret than indicators only involving a subgroup of observed variables.

This issue can be addressed by transforming the results of a classical exploratory factor analysis following a three steps procedure described in Costello and Osborne (2005), which assures that each observed variable contributes to at most one single factor. Examples of such an approach can be found in Heckman et al. (2013), von Stumm et al. (2009), Fiorini and Keane (2012) and Conti et al. (2014). In a first step, factors are rotated to form groups of items loading on (i.e. getting grouped into) certain factors. Then, in a second step, items that load on at least two factors with similar loadings (so-called double loadings) are dropped.¹³ Finally, in a third step, only items with loadings above a given threshold are assigned to the factor they belong to.

In the initial step of the exploratory factor analysis, factors are extracted by maximising the variance accounted for by the first and subsequent factors while forcing factors to be orthogonal. Any subsequent rotation of the factors leaves the subspace they generate unchanged, i.e. the optimisation solution of the factor analysis is not affected by the rotation procedure. A non-orthogonal rotation method (the oblique rotation or ‘promax’ method) is chosen as factors do not need to be constrained to be orthogonal to each other, especially in the case of extracting latent measures for skills (Conti et al. 2014). This rotation method is designed to give a simpler structure to the factors so that the loadings of the observed variables are closer to 1 or 0 (Costello and Osborne 2005).

Even after rotating the factors, however, some items might have still high loadings on several factors (i.e. double loadings). These items with double loadings are difficult to assign to a single factor and are therefore dropped from the analysis in a second step. The importance of removing double loadings is often assessed on the basis of the ratio between the second highest loading and the highest loadings (Costello and Osborne, 2005), so that items with a ratio above a given threshold are dropped.

Once factors are rotated and items with double loadings are dropped, in a third step, all loadings below a given threshold are assigned to 0. Items without any loading above the threshold will thus be dropped from the analysis. Due to the exclusion of items with double loadings, each remaining item loads above the threshold on one factor only. At the end of this process, each item is thus either dropped from the analysis, or assigned to the one and only factor on which it loads above the set threshold.

The three step procedure described above is first applied to the full set of items chosen for the exploratory factor analysis. After having excluded the double-loading items, as well as those items loadings below the threshold, the whole three step procedure is re-run on the subset of remaining items.

The algorithm converges and the process is finalised when no more additional items are dropped by the three step procedure. The final result thus consists of groups of items that are exclusively allocated to specific factors.

For each subset of items that are allocated to a specific factor, a simple, un-rotated, factor analysis is applied to extract the associated skill indicator and predict its values (the so-called factor scores)¹⁴. To obtain skill indicators with values ranging between 0 and 1, a logistic transformation is applied to the extracted factor scores. It has to be noted that, instead of using population weights which would have given a higher importance to bigger countries, this analysis uses the so-called 'senate weights', so that all countries have the same importance in the analysis.¹⁵ Senate weights in fact guarantee that all countries are equally represented in the computation of the overall statistics.

Choice of parameters

There is no universal statistical criterion for selecting the number of factors and parameters for the exploratory factor analysis.¹⁶ Using real as well as simulated data, Conti et al. (2014) show that the number of extracted factors strongly varies depending on the applied selection criterion. In our context, classical criteria also give different indications on the correct number of factors. On the one hand, the Kaiser's rule, the Scree Test and the additional variance explained by subsequent factors indicate that choosing 6 factors would be the appropriate decision (see Table A4 and A5).¹⁷ On the other hand, the Akaike (AIC) and the Bayesian information criterion (BIC) yield an optimal number of factors equal to 45 and 36, respectively¹⁸.

In the absence of clear and converging indications arising from the statistical tests applied, this work pursues a pragmatic approach, whereby factors are selected on the basis of the following criteria. First, given that the main purpose of this analysis is to identify the "key" set of skill factors that matter for performance on the job and for economic performance, their number is constrained to 10 or less factors. Second, these factors (and the items loading on them) need to be robust to changes in the definition of the sample, most notably across different set of countries, different subsets of items and different sample weights (population vs. senate weights) used for the exploratory factor analysis. Third, the sub-group of items loading on specific factors should not change when different numbers of factors are extracted, i.e. item loading should remain as stable as possible and not be affected by the number of factors chosen. Fourth, the resulting set of factors needs being coherent with economic intuition and their interpretation unequivocal. The fifth and final criterion used is that no factor can have less than 3 items loading on it.

Comparing the results obtained performing factor analysis of 4 up to 12 factors, the final specification chosen is the one featuring 6 factors. Three reasons back such a decision. First, the traditional criterion for determining the extraction of factors (Kaiser's rule and Scree Test) indicate to extract 6 factors, whereas other criteria indicate higher number of factors. Second, when extracting 7 factors, only two items load on the seventh factor, and this does not fulfil the criteria of having at least 3 items per factor (Conti et al. 2014). Third, the extracted six factors and the allocation of items to those factors are very robust to excluding groups of countries (Table A1)¹⁹, excluding certain items from the factor analysis (e.g. excluding section I from the PIAAC background questionnaire that is conceptually different from sections D, F and G), applying normal population weights instead of senate weights and using other factor extraction methods (maximum likelihood instead of principal factor extraction).²⁰

In addition to choosing the number of factors, one needs to determine two other thresholds for the three step procedure of the exploratory factor analysis. The first is the double loading threshold, which determines whether an item is excluded due to loading on at least two factors with similar loadings. Following existing studies, items where the ratio of second highest loading to highest loading is greater than 0.7, are excluded from the analysis (see Costello and Osborne 2005; Conti et al. 2014). Second, all loadings below a certain threshold are set to 0. The choice for this threshold results from a trade-off

between losing too many questions (because their loadings are not high enough) and assigning questions to factors they are not strongly associated with. In such cases, the literature suggests thresholds between 0.4 and 0.6, and this analysis thus uses the same 0.45 used in Conti et al. 2014. Experimenting with different thresholds for the loadings (0.4 and 0.5) and for double-loadings (0.8 and 0.6) leads to extremely similar results, and suggests that the basic factor structure is very robust. Evidently, the two threshold parameters create a discontinuity and generate some unavoidable instability in the model with respect to the exact number of items allocated to the six factors: small variations in the loadings of items that are close to these thresholds result in different decisions, depending on whether the loadings cross the threshold or not. Nevertheless, this only affects a small number of items whose loadings are very close to the thresholds (see Table A3 for the loadings of excluded and Table A2 for loadings of included items).

A number of additional robustness checks have been performed to guarantee that the results of the exploratory factor analysis are robust. These prove that the final factor structure (i.e. allocation of items to the six factors) does not depend on the rotation method applied to the extracted factors and that even using orthogonal rotations leads to the same structural solution shown in Table A2. The resulting six indicators are also robust to different approaches for the computation of indicator values. As described above, the values of the final skill indicators are computed by applying a simple factor analysis to each sub-set of items that (as a result of the exploratory factor analysis) exclusively load on one factor. In the baseline, the principal factor extraction method is used to extract the factors and the regression scoring method to predict the final factor scores.

To compute weights for the subset of items entering one indicator, OECD (2008) and OECD (2000) both suggest to either use principal component or principal factor extraction methods. Furthermore, the factor scores can be predicted by using the regression scoring or the Bartlett scoring method. Another possible approach for computing indicator values consists in applying a confirmatory factor analysis using the resulting allocation of items to factors from the exploratory factor analysis. The confirmatory factor analysis then uses maximum likelihood techniques to compute the final indicator values. For the present study, baseline indicators are compared with indicators computed following the alternative approaches mentioned (i.e. different extraction and scoring methods and confirmatory factor analysis) by computing the rank and the standard correlation of the baseline and the alternative indicators. Rank and standard correlations are always strongly significant and higher than 0.995, which further indicates the robustness of the constructed skill indicators.²¹

So far, the implementation of the exploratory factor analysis happens under the assumption that the scales of all 57 items are continuous, i.e. the difference between 2 consecutive values of the ordered item scale (from 1 to 5) is assumed to be constant across the scale. In Table A1 (column 2), this assumption is relaxed by computing a polychoric correlation matrix of the 57 included items and by applying the exploratory factor analysis to this matrix.²² The allocation of items to factors is very stable, the only difference being that one item drops from the sixth factor and three more items are included in the third factor. This further underlines the robustness of the baseline results.

Results

Table 2 presents the resulting six factors/skill indicators and the corresponding PIAAC items included in the construction of each indicator²³. Items are ordered according to the factor they are assigned to. As can be seen, 33 items are retained from the initial set of 57 items. To simplify the presentation of the matrix, these factors are already named according to the interpretation that is given to them.

Ranked on the basis of the total variance explained, the six factors identified are: *Information and Communication Technology (ICT) Skills*, *Readiness to Learn and Creative Problem Solving*, *Management and Communication*, *Self-Organisation*, *Marketing Skills* and *Science, Technology, Engineering and*

Mathematics (STEM) – quantitative Skills. Note that this ranking is influenced by the number of items assigned to the factor and is a feature of the item composition of the Survey of Adult Skills. All items are clearly assigned to their factor with loadings above 0.5 and low loadings on the remaining factors (Table A2). Out of the 33 retained items, only 3 of them have loadings below 0.52: ‘Negotiating with people’ (0.486) ‘Prepare charts, graphs or tables’ (0.508) and ‘Use a calculator’ (0.509). All three items are also those with relatively high loadings on other factors (0.3).

Table 2: 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 organization) 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
Marketing and Accounting	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
STEM-Quantitative skills	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: Authors' own compilation based on PIAAC.

The first factor, named *ICT Skills*, consists of 10 items with very high positive loadings and one item with a negative loading. The items with positive loadings all describe tasks associated with Information and Communication Technology use, from reading and writing emails to using word and excel or a programming language. This is the reason why this factor is interpreted as ICT skills. It has to be noted that the factor is also strongly associated with office jobs, as indicated by the remaining item, ‘physical activities’, which actually loads negatively on this factor.

The second factor, *Readiness to Learn and Creative Problem Solving*, consists exclusively of items that by construction in PIAAC are meant to measure this dimension, e.g. ‘Relate new ideas into real life’ or ‘Like learning new things’. This factor is very similar to the analogous one constructed using the normative typology detailed in Grundke et al. (2016a).

The third factor, *Management and Communication Skills*, gathers a more diverse set of items, from ‘teaching people’ to ‘planning others activities’. However, all these activities involve communicating with and managing other people, whether they are co-workers or not. This factor mixes items that are associated in the normative typology with *Managing* and *Interacting and Communicating*.

The fourth factor, *Self-organisational skills*, arises out of items that, as in the case of Readiness to Learn and Creative Problem Solving, are designed in PIAAC to measure these very dimensions. It includes items such as ‘Work flexibility - Speed of work’ or ‘Work flexibility – Sequence of tasks’ and replicates an indicator already included in the normative typology.

The fifth factor, *Marketing and Accounting Skills*, is a newly constructed indicator that does not correspond to any indicator proposed in the normative typology. ‘Reading financial statements’, ‘Calculating costs or budgets’ and ‘Selling products or services’ are associated with this factor, which is therefore interpreted as relating to Marketing and Accounting skills. In addition, ‘Using a calculator’ is associated with this factor. Although this item also loads on ‘ICT contents’ and ‘STEM contents’ (with loadings close to 0.25), it seems that calculators are mainly used for marketing and accounting purposes.

The sixth factor, *STEM-quantitative Skills*, is not in the normative typology either. Like *Marketing and Accounting Skills*, it involves numeric tasks such as ‘Use simple algebra or formulas’ or ‘Use advanced math or statistics’, but the tasks in *STEM-quantitative* skills are more complex and less specific than those loading on the previous factor. This factor is interpreted broadly as skills necessary for Science, Technology, Engineering and Mathematics.

Characterising skills by workers' and jobs' main features: cross-country statistics by age, gender, occupation, firm size and industry

In what follows, a number of stylised facts are presented. These portray the cross-country differences in the skill endowment of the workforce in terms of the six task-based skill factors identified, plus the cognitive skills formally assessed in PIAAC. In the impossibility to display endless charts and tables picturing all the possible combinations of workforce characteristics and skill indicators considered, a selection has been made on the basis of their possible policy relevance. In the figures shown in this section, countries are separated into two groups, the countries that participated in the first round of PIAAC and the ones that participated in the second round. The figures all display: on the y-axis countries' average scores for the corresponding skill and the respective sub-group of workers; on the x-axis, the different sub-groups of workers presented (along the occupation, industry, firm size, age and gender dimension). The height of each bar represents the cross-country dispersion of average scores (within the respective country group) for the worker group category considered.

Figure 1a: Numeracy proficiency by industry

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and gender specific averages, by industry. Each bar shows the country exhibiting the minimum and maximum average country-industry-gender value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 1b: Numeracy proficiency by age

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and sector specific averages, by age cohorts. Each bar shows the country exhibiting the minimum and maximum average country-sector-age group value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 1a and Figure 1b show the distribution of numeracy proficiency across PIAAC countries by industry and age, respectively. Figure 1a shows that the countries in the second round of PIAAC have slightly lower average numeracy scores and larger cross-country-differences than the countries in the first round. However, the patterns observed are similar for both country groups. First, the dispersion of numeracy skills appears to be slightly higher within industry than across industries. The highest average numeracy scores are found within the Finance and Insurance and the Real Estate and Other Services industries. Secondly, for both rounds of PIAAC, the within-industry dispersion of numeracy skills is slightly larger for the female cohorts than for the male cohorts.

Heterogeneity in numeracy skills also emerges within as well as across different age groups, and depending on the sector of activity (Fig. 1b). The largest cross-country differences can be observed among manufacturing workers aged 24 or less for the first round of PIAAC, and among services workers aged more than 55 for the second round of PIAAC. The highest average scores are displayed by the young adult group, i.e. those aged between 25 and 34. This likely mirrors the moment in life in which the highest cognitive development can be attained through schooling and that surveyed individuals may still enjoy the effect of recent schooling. Combining Figure 1a and 1b, it seems that the high average numeracy values in the Finance and Insurance industries might also reflect the fact that many young and highly educated workers are attracted by these industries. Overall, the large cross-country differences coupled with basically the same countries appearing at the top or the bottom of the observed distributions, calls for an analysis of the way in which labour market, education and training policies shape the patterns observed.

Figure 2: Problem solving proficiency by industry

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and gender specific averages, by industry. Each bar shows the country exhibiting the minimum and maximum average country-industry-gender value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

The distribution of problem solving skills across countries is displayed in Figure 2 in terms of industry and gender. Across industries, problem solving skills mirror the same patterns seen in the case of numeracy skills. In particular, the highest average scores for both male and female are found within the Finance and Insurance and the Real Estate and Other Services industries. Problem solving skills generally appear less heterogeneous across countries included in the first round of PIAAC than across countries included in the second round.

Figure 3a: ICT skills by industry

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and gender specific averages, by industry. Each bar shows the country exhibiting the minimum and maximum average country-industry-gender value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 3b: ICT skills by occupation

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and sector specific averages, by occupational category. Each bar shows the country exhibiting the minimum and maximum average country-sector-occupation value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

In the current knowledge-based and progressively more globally integrated and digitalised paradigm in which countries and industries operate, ICT skills can be important for economic performance. As seen in both Figure 3a and 3b, ICT skills vary across industries as well as occupations. The basic pattern for the distribution of ICT skills across industries is similar to the one of numeracy and problem solving, whereby the highest average scores are observed in the case of Finance and Insurance and the Real Estate and Other Services industries. However, the differences between male and female are quite stunning for the construction and transport and storage industries as well as heavy manufacturing, as female workers in

those industries show much higher values than their male counterparts. The might be due to the fact that female and male workers in those industries carry out different occupations. In Figure 3b, in line with expectations, high-skill occupations display higher ICT skills than low skill occupations. Also, median country values of high-skill occupations are very high and are close to top values, thus suggesting that a big digital divide exists between high skilled workers of different countries. Within occupations, the differences between countries are very large, and indicate a strong heterogeneity in the use of ICT technology within occupations.

Figure 4: Managing and Communication skills by firm size

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and firm size specific averages, by sector. Each bar shows the country exhibiting the minimum and maximum average country-sector-firm size value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 4 shows the distribution of Managing and Communication skills across PIAAC countries by firm size and economic sector. The observed patterns are similar for both rounds of PIAAC. First, workers in the services sectors generally show higher average scores for managing and communication skills than in the manufacturing and utilities sectors. Second, there is a clear indication that workers in bigger firms are better equipped with managing and communication skills than workers in smaller firms, especially in the services sector. In the manufacturing and utilities sector, this pattern is less pronounced for the small and medium size firms, but firms with more than 250 employees also show higher managing and communication skills compared to small and medium size firms.

Figure 5: Marketing and accounting skills by occupation

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and sector specific averages, by occupational category. Each bar shows the country exhibiting the minimum and maximum average country-sector-occupation value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

As can be seen from Figure 5, *Marketing and accounting* skills differ enormously across but not much within occupations. Managers, technicians, clerical support as well as services and sales workers display the highest average scores indicating that marketing and accounting tasks are not confined to only a single group of occupations. The observed patterns are similar for both rounds of PIAAC.

Figure 6: Self-organisation skills by occupation

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and sector specific averages, by occupational category. Each bar shows the country exhibiting the minimum and maximum average country-sector-occupation value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 6 shows that *Self-organisation* skills vary substantially across as well as within occupations, and by economic sector. Across economic sectors, the manufacturing and utilities sector displays higher average values for the higher skilled occupations than the services sector. However, for lower skilled occupations, the services sector displays higher average self-organisation skills than the manufacturing and utilities sector. Within the same occupations, the differences between countries are larger for manufacturing and utilities industries.

Figure 7a: Readiness to learn and creative problem solving by industry

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and gender specific averages, by industry. Each bar shows the country exhibiting the minimum and maximum average country-industry-gender value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

Figure 7b: Readiness to learn and creative problem solving by firm size

Source: Authors' own compilation based on PIAAC.

Note: Figures are based on country and firm size specific averages, by sector. Each bar shows the country exhibiting the minimum and maximum average country-sector-firm size value. All country - worker group cells with less than 25 observations in PIAAC were excluded from the analysis to reduce measurement error.

As can be seen from Figure 7a, while countries differ in the *Readiness to learn and creative problem solving* of their workers, differences are not marked across industries. The fact that countries at the top and the bottom of the distribution are always the same triggers the question of whether cultural issues may be at stake. While industry-specific average scores are generally more dispersed across the countries in the first round of PIAAC, the dispersion for female workers is generally higher than the one for male workers. Focussing on the distribution across different firm sizes, Figure 7b shows similar patterns across firm sizes as in the case of the Managing and Communication skills. The services sector attracts workers with higher average readiness to learn and creative problem solving scores than the manufacturing and utilities sector. Moreover, there is a clear indication that workers in bigger firms are better equipped with this self-reported learning ability than workers in smaller firms.

Exploring the relationship between skills, economic performance and GVCs

The stylised facts highlighted so far suggest that the cross-country skill endowment of the workforce differs according to structural features like industry and firm size, as well as worker-specific features like occupation, age and gender. This descriptive evidence, coupled with the evidence provided in Grundke et al. (2016a), suggests investigating the extent to which different skills, and the different moments of their distributions, relate to economic performance and integration into global value chains.

To shed light on these issues, the present section shows the results of a number of conditional correlations implemented at the country-industry level between skill endowment-related indicators and measures of economic performance and participation in international markets. To this end, a database was constructed combining the skill measures based on PIAAC with industry measures of economic performance and international integration for the year 2011, taken from the OECD TiVA 2015 database. This combined database includes 31 countries and the chosen level of industry aggregation is the 18 TiVA industry level.²⁴²⁵ Country-industry-specific skill endowment is measured using several moments of the country-industry distribution (at the TiVA 18 industry level) of cognitive skills, task-based skills and personality traits. Economic performance and international integration are measured using labour productivity as well as selected trade in value added indicators, respectively. The aim is to explore the extent to which different types of skills and different moments of the country-industry skill distribution relate to productivity and integration into GVCs.

Skills and labour productivity

To assess the link between skills and economic performance, this paper estimates the following OLS regression for the year 2011 using two measures of labour productivity as dependent variables, one in value added terms (i.e. value added in Million USD per employee) and the other in output terms (i.e. output in Million USD per employee).

$$\ln(\text{productivity})_{i,k} = \alpha_0 + \alpha_1 \text{Skill}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_k + u_{i,k}$$

For country i and industry k .

The independent variable *Skill* stands for one moment of the skill distribution at the country-industry level. The analysis is conducted for each cognitive skill and each task-based skill indicator separately, and regressions are estimated for different single moments of the country-industry skill distribution (mean, standard deviation, 10th percentile, median and 90th percentile).²⁶ In additional specifications, the mean and the standard deviation of the country-industry distribution of each skill enter the regression jointly. To allow for comparison of the coefficients, all skills indicators are rescaled so that they are defined in an interval between 0-100. All specifications include additional country-industry level control variables x , namely:

- Physical capital intensity, measured as the net fixed assets in Thousand USD per worker (in log terms). Figures are taken from the OECD's Annual National Accounts database;
- Skill intensity, defined as the share of medium and high-skilled workers, as measured by educational attainment, taken from the World Input-Output Database (WIOD)²⁷;
- Expenditure in research and development (R&D) in Billion USD, taken from the OECD ANBERD database.²⁸

To control for all unobserved characteristics at the country level as well as the industry level, all regressions include dummy variables for countries (μ_i) and industries (δ_k). Thus, by controlling for the unobserved characteristics of each industry (that are similar across countries), this specification takes the within industry perspective and investigates how changes in the independent variables within each industry (across countries) affect the labour productivity of industries on average. An additional specification excludes industry dummy variables to investigate how the country-industry skill distribution relates to economic performance across industries, i.e. to see whether industries that differ in their skill endowments also differ with respect to their labour productivity. Robust standard errors are clustered at the country-level. Country-industry cells having fewer than 25 observations in the Survey of Adult Skills are excluded from the analysis, to reduce possible measurement error in the skill variables.

Table 3 shows the conditional correlations that emerge for several points of the skills' distributions and labour productivity, controlling for all unobserved industry characteristics that are similar across countries (i.e. including dummy variables for industries). These correlations look at the relationship between changes in industry-specific skill endowment and labour productivity in the same industry. In contrast, Table A6 in Appendix A shows the results of the correlations obtained when taking an across-industries perspective (i.e. by excluding the industry dummy variables). These correlations allow verifying whether industries that differ in their specific skill endowment also differ in their labour productivity. In both tables, the first five columns show the results from single specifications, i.e. each cell corresponds to a single specification obtained in such a way that only one single moment of the distribution of one single skill indicator enters the regression at a time. Conversely, under the heading "Combined specifications", the last two columns report the estimation results obtained entering both the mean and the standard deviation values of the skill variable considered.

Looking at the within industry perspective in Table 3, a significant and positive correlation emerges between labour productivity and the mean of assessed cognitive skills, for both measures of labour productivity (Panel A and B). An increase of 1 point in the industry mean of assessed cognitive skills (which due to the rescaling to the 0-100 interval corresponds to a 5 point increase in the PIAAC scale for assessed cognitive skills), corresponds to an increase in labour productivity by around 3%. Of the task based skills, only the industry mean of ICT skills shows a significant positive correlation with labour productivity. This is however of smaller magnitude than the one of cognitive skills (a 1 point increase in the mean leads to a 1% increase in productivity). The size of the coefficients for the mean STEM-quantitative skills is of the same size of ICT skills, but is only significant when controlling also for the standard deviation, in the combined specification (in the last two columns). When measuring labour productivity in output terms in Panel B, the mean of Readiness to Learn and Creative Problem Solving skills is also significantly and positively associated with productivity.

Overall, the correlation coefficients between assessed cognitive skills and labour productivity are generally higher in magnitude than those for the task-based skills and personality traits, which become even insignificant in the case of Management and Communication, Marketing and Accounting and Self-Organization skills. One possible explanation might be that, in contrast to assessed cognitive skills, the task-based skill indicators measure workers' skills only indirectly, through the tasks they carry out on the job (or in terms of self-reported characterisations, in the case of personality traits). This may lead to measurement error and to a possible attenuation bias of the coefficients for the task-based skills and personality traits towards zero. Another explanation might be that cognitive skills play a more important role in explaining within industry variation in labour productivity than task-based skill indicators, because cognitive skills measure a more general and industry- and task-independent set of skills. Task-based skill indicators measure skills that are related to the specific task-content of jobs, and not all industries require the same set of job-tasks and the corresponding skills. For example, increasing STEM-quantitative skills in an industry that does not require those skills might have no effect on productivity in that industry. Thus, when taking a within industry perspective, certain task-based skills might have no effects on productivity in certain industries, i.e. they exhibit insignificant average effects.²⁹ Against this background, it is remarkable that ICT skills have a significant and positive effect on labour productivity in all industries, irrespective of their characteristics.

Table 3: Correlations between skill indicators and labour productivity at the country-industry level

Panel A: Log of the value added per employee	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.029**	0.009	0.024	0.009	0.033**	0.036**	0.031
Numeracy	0.022*	0.008	0.015	0.008	0.022*	0.028**	0.025*
Problem solving	0.032**	0.045	0.023	0.008	0.039***	0.033**	0.049
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.011***	0.005	0.004***	0.002	0.004	0.011***	0.003
STEM	0.01	0.009	0.003	0.002	0.002	0.011*	-0.002
Marketing/Accounting	0.004	0.022*	0.002	-0.005	0.004	0.002	0.02
Managing/communication	0.008	-0.005	0.003	0.005	0.001	0.008	-0.007
Self-organisation	-0.004	-0.001	-0.002	-0.002	-0.005	-0.004	-0.003
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.007	0.009	0.006	0.002	0.006*	0.007	0.009

Panel B: Log of output in USD per employee	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.039*	-0.019	0.035*	0.017	0.029	0.041*	0.006
Numeracy	0.035**	-0.024	0.027*	0.019**	0.017	0.035**	-0.002
Problem solving	0.028*	0.033	0.019	0.011	0.032**	0.029*	0.036
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.011*	-0.001	0.004	0.003	0.005	0.011*	-0.002
STEM	0.007	0.005	0.002	0	0.001	0.008	-0.003
Marketing/Accounting	0.007	0.019	0.003	-0.001	0.004	0.005	0.014
Managing/communication	0.011	0.001	0.005	0.008	0.003	0.011	-0.002
Self-organisation	-0.01*	0.009	-0.005	-0.007	-0.007*	-0.009*	0.004
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.015*	0.01	0.011	0.006	0.01**	0.015*	0.01

Source: Authors' own compilation.

Note: The dependent variable is the log of labour productivity measured as value added per employee (Panel A) and as output in USD per employee. All specifications are estimated using OLS and include dummies for countries and industries as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure). Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one single skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits the 25th and 75th percentiles are considered, as the 10th and 90th percentiles are uninformative due to scarce variation). The heading "Combined specifications" contains specifications including both the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

When taking an across industry perspective (Table A6), the correlation of labour productivity with the mean of all task-based skills and personality traits becomes positive and significant (except for self-organisation which has no significant effect). For example, an industry that has a one point higher mean in STEM-quantitative skills shows on average a 3.7% higher labour productivity (as measured by value added per worker). However, the positive correlation coefficients for assessed cognitive skills are still higher in absolute value than the ones for the task-based skills. This may indicate that assessed cognitive skills are a more adequate measure for the general skills of workers. However, the results in Table A6 show robust evidence that industries with a higher mean in task-based skills also have a higher labour productivity, *ceteris paribus* (i.e. controlling for the intensity of industries in capital, skilled labour, research and development, and unobserved country-specific factors). This might indicate that the specialisation of industries in certain tasks requiring specific task-based skills increases their productivity.

Another feature that emerges from the analysis is that the shape of an industry's skill distribution matters for productivity. The correlation of productivity in value added terms with the 90th percentile of the cognitive skill distributions exhibits statistically significant and higher coefficients than that of the 10th percentile. Due to the use of industry-level data, these results may reflect underlying firm level dynamics like, for instance, that more productive bigger firms and firms at the frontier, which influence industry-level productivity importantly, attract workers from the upper part of the skill distribution. In contrast, for productivity in output terms, the described importance of the upper part of the industry skill distribution is not supported by the results.

Finally, the major explanatory variables, i.e. physical capital intensity, R&D and human capital intensity, show the expected relationship with productivity (see Table A9 in Appendix A). Productivity increases with rising intangible capital intensity. A billion USD increase in R&D expenditures corresponds

to an increase of 0.5% of value added per worker, but exhibits no relationship with productivity in output terms. This may reflect the important role of R&D activities in creating value added. The fact that human capital intensity (measured by educational attainment) appears insignificant for value added per worker and significant at the 10% level for output per worker stands up for the use of indicators based on the Survey of Adult Skills, as they more accurately measures the human capital of the workforce.

Skills and trade in value added

To assess the link between skills and international integration into global value chains, the constructed PIAAC-TiVA database for 31 countries and 18 TiVA industries was extended to also include bilateral trade flows in gross and value added terms (for the year 2011) with 61 partner countries included in the OECD TiVA 2015 database. This paper estimates the following bilateral country-industry (gravity) model for trade in gross and value added terms for the year 2011.

$$\ln(tradeflow)_{i,j,k} = \alpha_0 + \alpha_1 Skill_{i,k} + x'_{i,k} \beta + y_{j,k} \pi + z_{i,j} \gamma + \mu_i + \theta_j + \delta_k + u_{i,j,k}$$

For home country i , foreign country j and industry k .

The list of dependent variables (*tradeflow*) includes:

- Exports in gross terms (EXGR; in Million USD) from home country i to foreign country j in industry k ;
- Two indicators of forward linkages, namely: the domestic value added embedded in gross exports (EXGR_DVA; in Million USD) of home country i in industry k to foreign country j ; and the domestic value added of home country i and industry k embedded in foreign final demand of country j (FFD_DVA; in Million USD);
- Two indicators used as proxies of backward linkages, namely: foreign value added from country j embedded in the final demand of domestic industry k in home country i (DFD_FVA; in Million USD) and foreign value added from country j embedded in exports of domestic industry k in home country i (EXGR_FVA; in Million USD).

All dependent variables enter the regressions in logs. As in the productivity regressions before, the independent variable *Skill* stands for one moment of the skill distribution at the country-industry level. The analysis is conducted for each cognitive skill and each task-based skill indicator separately. Regressions are estimated for different single moments of the country-industry skill distribution (mean, standard deviation, 10th percentile, median and 90th percentile).³⁰ In additional specifications, the mean and the standard deviation of the country-industry distribution of each skill enter the regression jointly. To allow for comparison of the coefficients, all skills indicators are rescaled so that they are defined in an interval between 0-100.

Country-industry control variables (x) accounting for physical capital intensity, skill intensity and R&D expenditure enter all specifications, as done in the productivity regressions. In addition, barriers to trade (z) are controlled for by including the standard time invariant bilateral trade cost variables used in the literature, namely: distance, contiguity, common language, common coloniser, past and current colonial links and being the same country. These variables are taken from the Centre d'Études Prospectives et d'Informations Internationales (CEPII)³¹ database.

Additional control variables at the country-industry level (x and y) necessary for standardisation of the dependent variables in this type of sectoral gravity equations (Nogueira 2012) are also included, as follows:

- The regressions using gross exports and domestic value added embedded in exports (EXGR_DVA) as dependent variable additionally include the log of production of the exporting country i in industry k as well as the log of the final demand in the importing country j in industry k . Production is used instead of value added for the second dependent variable, as EXGR_DVA includes the domestic value added created by all industries in the domestic country (embedded in exports in industry k), not only the direct value added coming from the same industry.
- The regression featuring domestic value added in foreign final demand (FFD_DVA) as the dependent variable includes the log of domestic value added of the exporting country i for industry k , but not the log of final demand in the importing country j for industry k . This is done as FFD_DVA is computed based on total foreign final demand, which is controlled for in the partner-country dummies. In contrast to EXGR_DVA, FFD_DVA only includes the direct value added created in industry k in the home country, and this ends up in the total final demand of the foreign country. Thus, it is reasonable to control for the value added in the home country i and industry k as an independent variable.
- The regression with foreign value added embedded in domestic final demand (DFD_FVA) as the dependent variable includes the log of domestic final demand in country i for industry k , but not the log of value added in the foreign country for industry k . Again, this is done as DFD_FVA is computed based on total foreign value added (which is controlled for in the partner-country dummies).
- The regression with the dependent variable foreign value added embedded in exports (EXGR_FVA) includes the log of domestic production of the exporting country i for industry k , but not the log of value added in the foreign country j for industry k . This is done as EXGR_FVA is computed based on total foreign value added (which is controlled for in the partner-country dummies).

To control for all unobserved characteristics at the home and partner country as well as the industry level, all regressions include dummy variables for home countries (μ_i), partner countries (θ_j) and industries (δ_k).³² Thus, by controlling for all unobserved characteristics of each industry (that are similar across countries), this specification takes a within industry perspective and investigates how changes in the independent variables within each industry (across countries) affect the integration of industries into GVCs, on average. However, in an additional specification the dummy variables for industries are excluded to investigate how the country-industry skill distribution relates to integration into GVCs across industries, i.e. this specification investigates whether industries that differ in their skill endowments also differ with respect to their integration into GVCs. Robust standard errors are clustered at the exporter-importer level. Country-industry cells having fewer than 25 observations in the OECD Survey of Adult Skills are excluded from the analysis, to reduce possible measurement error.

Table 4 and 5 show the conditional correlations that emerge for several moments of the industry skills' distributions and trade in value added indicators, when controlling for all unobserved industry characteristics that are similar across countries (i.e. including dummy variables for industries). This means that in these correlations one takes a within industry perspective and asks whether a change in the industry specific skill endowment affects trade integration in the same industry. In contrast, Table A7 and A8 in the Appendix A show the results of the correlations obtained when taking an across industries perspective (i.e. excluding the industry dummy variables). This allows seeing whether industries that differ in their specific skill endowment also differ with respect to their integration into GVCs. In all tables, the first five columns show the results from single specifications, i.e. each cell corresponds to a single specification obtained in such a way that only one single moment of the distribution of one single skill indicator enters the regression specification at a time. Conversely, under the heading "Combined specifications", the last two columns report the estimation results obtained entering both the mean and the standard deviation values of the skill variable considered.

From the within industry results in Table 4, it can be seen that cognitive skills, ICT skills, Managing and Communication skills as well as Readiness to Learn are positively related to exports (in gross and value added terms in Panel A and B, respectively) and to forward integration into GVCs (Panel C). The coefficients for the industry means of these skills are significant and positive in almost all cases. Positive correlations are stronger the cognitive skills than for the other skill indicators, as already observed in the case of the productivity regressions.

Table 4: Correlations between skills and exports (in gross and value added terms) and forward linkages, at the bilateral country-industry level

Panel A: Log of Gross Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.058***	0.01	0.052***	0.026***	0.076***	0.07***	0.053***
Numeracy	0.045***	-0.017*	0.053***	0.018***	0.025***	0.049***	0.012
Problem solving	0.054***	-0.004	0.015**	0.065***	0.063***	0.054***	0.001
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.004	0.017**	-0.003**	0	0.01***	0.003	0.016**
STEM	-0.011***	-0.004	-0.014***	0.018***	-0.005***	-0.015***	0.012
Marketing/Accounting	-0.005	0.039***	-0.003*	-0.009***	0	-0.01***	0.049***
Managing/communication	0.005	0.034***	0	-0.002	0.008***	0.003	0.033***
Self-organisation	-0.018***	-0.043***	-0.02***	-0.006**	-0.016***	-0.024***	-0.055***
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.011***	0.025***	0.002	-0.002	0.01***	0.011***	0.025***

Panel B: Log of Value Added Embedded in Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.062***	0.018	0.055***	0.026***	0.087***	0.077***	0.064***
Numeracy	0.048***	-0.012	0.055***	0.018***	0.03***	0.054***	0.021**
Problem solving	0.061***	0.006	0.02***	0.066***	0.071***	0.061***	0.013
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.007**	0.015**	-0.002	0.002	0.011***	0.007**	0.015**
STEM	-0.005	0.001	-0.012***	0.021***	-0.002	-0.008*	0.01
Marketing/Accounting	-0.002	0.045***	-0.002	-0.009***	0.002	-0.008**	0.052***
Managing/communication	0.008***	0.032***	0.002	-0.001	0.01***	0.007**	0.031***
Self-organisation	-0.012***	-0.05***	-0.016***	-0.002	-0.014***	-0.018***	-0.059***
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.011***	0.023***	0.003	-0.002	0.008***	0.011***	0.023***

Panel C: Log of Value Added Embedded in Foreign Final demand	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.007*	-0.001	0.006**	0.004*	0.013***	0.007*	0.003
Numeracy	0.009***	-0.01**	0.013***	0.003*	-0.001	0.008**	-0.005
Problem solving	0.003	0.022**	-0.003	0.006*	0.013***	0.004	0.022***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	-0.001	0.015***	-0.001*	-0.002***	0.003***	-0.002	0.015***
STEM	-0.009***	0	-0.007***	-0.002*	-0.002***	-0.015***	0.015***

Marketing/Accounting	-0.002*	0.011***	-0.001	-0.005***	-0.001*	-0.004***	0.015***
Managing/communication	0.005***	0.016***	0.001	-0.001	0.006***	0.004***	0.015***
Self-organisation	-0.01***	-0.004	-0.008***	-0.005***	-0.007***	-0.011***	-0.01***
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.005***	0.012***	0.002	0.001	0.004***	0.005***	0.012***

Source: Authors' own compilation.

Note: The dependent variables are: the log of bilateral gross exports (Panel A), the log of bilateral value added exports (Panel B) and the value added embedded in foreign final demand (Panel C) for industry k in home country i and partner country j . All specifications are estimated using OLS and include dummies for home country, for partner country and for industries as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure) and bilateral trade cost variables (bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). In Panel A and B, the gravity variables log of production in home country i and industry k as well as log of final demand in partner country j and industry k enter the regression. In Panel C, the independent variable log of value added in home country i and industry k enters the specification. Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits 25th and 75th percentiles are instead used). Under the heading "Combined specifications", specifications include the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

These results suggest that cognitive skills, ICT skills, managing and communication skills and readiness to learn are fundamentally linked to international integration in all industries, irrespective of the characteristics of each industry. Cognitive skills as well as the use of ICT, Managing and Communication skills and readiness to learn may be necessary for firms in all industries to absorb, learn and share new knowledge across borders, and to participate and grow in markets in which they have little or no previous experience.

In contrast, the industry means of the other task-based skills (STEM-quantitative, Marketing and Accounting and Self-Organisation) seem to exhibit no relationship or even a negative link with integration into GVCs, when taking a within industry perspective. For example, holding all unobserved industry characteristics constant, an increase in the mean of STEM-quantitative skills shows a small negative correlation with exports and forward linkages. The reason for this might be that not all industries require the same set of job-tasks and the corresponding skills. Increasing STEM-quantitative skills in an industry that does not require those skills might not have a productivity enhancing effect (as seen in Table 3) and, thus, might not have a positive effect on exports and forward linkages. This explains the insignificant or even negative average correlations in Table 4 for the task-based skills STEM-quantitative, Marketing and Accounting and Self-Organisation.

When taking an across industry perspective (Table A7), the correlation of forward linkages with the mean of all task-based skills (except for Self-Organisation) becomes positive and significant (Panel C). This indicates that across industries the specialisation of an industry in a certain task increases its productivity (as seen in Table A6) and, hence, its forward integration into GVCs. For example, an industry that has a one point higher mean in STEM-quantitative skills shows on average a 2.6% higher domestic value added embedded in foreign final demand. These results are less pronounced when using exports in gross or value added terms as dependent variables, and the coefficients of Marketing and Accounting and Management and Communication skills become even negative. This may be explained by the fact that exports in gross and value added terms do not take into account the indirect exports of services sectors through intermediate input supply to domestic manufacturing sectors. Because services sectors are more intensive in Marketing and Accounting as well as Management and Communication skills and have very low direct exports compared to their indirect component, using exports in gross and value added terms may not be able to capture the true underlying relationships. Conversely, using the domestic value added

embedded in foreign final demand as dependent variable, one captures the indirect exports of services sectors and finds that industries that specialise in Marketing and Accounting and Management and Communication tasks (and thus require the corresponding skills) also increase their integration into GVCs.

The analysis further suggests that the shape of the industry skills' distribution matters for integration into GVCs, when taking the within and also when taking the across industries perspective. The correlation of exports (in gross and in value added terms) and forward linkages with the upper part of an industry's skill distribution (90th or 75th percentile) exhibits statistically significant and higher coefficients with the lower part (10th or 25th percentile). This holds for cognitive as well as task-based skills and personality traits. These results may reflect underlying firm level dynamics like, for instance, that more productive bigger firms and firms at the frontier, which influence industry-level productivity importantly, attract workers from the upper part of the skill distribution (OECD, 2015).

When looking at backward linkages and taking a within industry perspective, a significant positive link between cognitive skills and readiness to learn for the two different measures for backward linkages is found (Table 5). Remarkably, cognitive skills seem to matter relatively more in backward linkages, which are linked to further exporting activities (foreign value added embedded in exports), than for backward linkages ending up in domestic final demand. For the task-based skills ICT, STEM-quantitative and Marketing and Accounting the mean of the industry skill distribution shows a negative and significant correlation with foreign value added embedded in domestic final demand. The same does not hold for ICT and Marketing and Accounting skills in the case of imported intermediate inputs that are then included in exported goods (foreign value added embedded in exports). This might signal that offshoring is indeed reducing domestic tasks in ICT and Marketing and Accounting for all industries and irrespective of the characteristics of each industry, if the offshoring does not lead to further exporting activities. Regarding STEM-quantitative skills, offshoring within an industry seems to reduce the domestic requirement for these task-specific skills on average, regardless of whether offshoring leads to further exporting or not.

Table 5: Correlations between skills and backward linkages at bilateral country-industry level

Panel A: Log of Foreign Value Added in Domestic Final Demand	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.024***	-0.002	0.024***	0.009***	0.022***	0.027***	0.015
Numeracy	0.01**	-0.007	0.017***	0.002	-0.001	0.01*	-0.001
Problem solving	0.023***	0.025**	0.016***	0.017***	0.021***	0.023***	0.027**
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	-0.01***	-0.011***	-0.005***	-0.003***	-0.004***	-0.01***	-0.01**
STEM	-0.013***	0.003	-0.011***	-0.003	-0.004***	-0.022***	0.026***
Marketing/Accounting	-0.009***	0.007	-0.001	-0.013***	-0.005***	-0.011***	0.017***
Managing/communication	0	0.011**	0	-0.002	0	-0.001	0.011**
Self-organisation	-0.022***	0.005	-0.013***	-0.014***	-0.014***	-0.023***	-0.007
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.006***	0.014***	0.004**	0.001	0.002	0.006***	0.014***

Panel B: Log of Foreign Value Added in Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.072***	-0.036***	0.054***	0.037***	0.069***	0.074***	0.009
Numeracy	0.073***	-0.05***	0.065***	0.04***	0.041***	0.072***	-0.005
Problem solving	0.026***	-0.025**	-0.009**	0.043***	0.03***	0.026***	-0.022**
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0	0.052***	-0.002**	-0.003***	0.01***	-0.001	0.052***
STEM	-0.007***	0.008**	-0.006***	-0.001	-0.001	-0.016***	0.024***
Marketing/Accounting	-0.001	0.053***	-0.001	-0.006***	0.002*	-0.008***	0.06***
Managing/communication	-0.001	0.027***	-0.003***	-0.006***	0.006***	-0.002	0.027***
Self-organisation	-0.014***	-0.026***	-0.012***	0	-0.011***	-0.017***	-0.034***
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.003	0.036***	-0.002	-0.005***	0.012***	0.003	0.036***

Source: Authors' own compilation.

Note: The dependent variable is the log of foreign value added from partner country j in domestic final demand of industry k in home country i (Panel A) and the log of foreign value added from partner country j in exports of industry k in home country i (Panel B). All specifications are estimated using OLS and include dummies for home country, for partner country and for industries as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure) and bilateral trade cost variables (bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). In Panel A, the log of final demand in home country i and industry k enters the regression. In Panel B, the independent variable log of production in home country i and industry k enters the specification. Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one single skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits the 25th and 75th percentile instead of the 10th and 90th are used). Under the heading "Combined specifications", specifications include the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

When taking an across industries perspective (Table A8), the results for cognitive skills become even more pronounced compared to the within industry analysis in Table 5. Industries with higher means for cognitive skills have lower backward linkages that end up in domestic final demand, but have much higher backward linkages that lead to further exporting activities. However, regarding the task-based skill indicators and readiness to learn, industries with a higher share of foreign intermediate inputs, irrespective of whether those inputs are used for the domestic final demand or for exporting, also have a lower requirements of task-based skills. This means that across industries offshoring may lead to a reduction in the intensity of industries in domestic tasks. The only exception is the STEM-quantitative skills, which are required more when the increasing backward linkages lead to further exporting activities.

Finally, the country-industry control variables (i.e. physical capital intensity and R&D expenditure) show the expected relationships with the dependent variables (see Table A10 in Appendix A). Integration into international markets increases with rising capital intensity (Table A9). A billion-increase in R&D expenditures corresponds to higher value added embedded in exports as well as in final demand by 0.4% and 0.2%, respectively. However, R&D expenditure relates negatively with backward linkages. This reflects the important role of R&D activities in creating value added and substituting for imported value added embodied in intermediate inputs. The fact that human capital intensity (measured by educational attainment) appears insignificant might depend from the fact that the specification already controls for the actual cognitive skills of workers (using the indicators based on the Survey of Adult Skills). Controlling for a more accurate measure of skills, human capital measured by educational attainment might proxy for other individual characteristics.

The results presented thus far are robust to changes in the specifications. Most importantly, the size of the coefficients does not change, when country-industry control variables are excluded (Table A11 and A12). However when including these controls, the sample size gets reduced from 466 to 256 observations in the productivity regressions, and from around 27 000 to around 15 000 observations in the trade regressions.³³ The fact that results do not change when specifications are estimated for the full sample of observations (i.e. without the industry controls) indicates that the results are not affected by sample selection bias (Table A11 and A12).³⁴ In additional robustness checks, where either additional dummy variables that control for all omitted aggregated sector characteristics (in the home and the partner country) or bilateral country-dummies are added, results also hold.

Although this study controls for a wide range of explanatory variables and unobserved country and industry characteristics (using dummy variables), it is difficult to identify a causal link from skill supply at the country-industry level to the performance of industries in GVCs. This is due to two main reasons. The first relates to the cross-sectional nature of the data, which do not allow to sufficiently control for unobserved country-industry characteristics that might influence skills supply as well as economic outcomes. The second relates to the endogenous nature of the economic processes analysed. If workers are mobile between industries, changes in the economic performance and participation in GVCs of these industries might influence the allocation of workers across industries within a given country and, thus, the skill supply at the country-industry level.³⁵

Conclusions

This study uses data from the Survey of Adult Skills (PIAAC) and an advanced exploratory factor analysis to extract six task-based skill indicators that are comparable across 31 countries and are clearer to interpret and sharper to distinguish from each other than the ones extracted by previous literature. These six new task-based skill indicators are: *information and communication technologies' (ICT) skills*; *readiness to learn and creative problem solving*; *managing and communication*; *self-organisation*; *marketing and accounting*; and *science, technology, engineering and mathematics (STEM)–quantitative skills*. Together with the three assessed cognitive skills contained in PIAAC (i.e. numeracy, literacy and

problem solving), these six new skill indicators are used to describe the skills distribution of workers across occupations, industries and countries. Furthermore, this study also combines the extracted skill data from PIAAC with the OECD TiVA database to investigate how different skills and their distributional moments at the country-industry level relate to the performance and integration of industries into global value chains.

This study bears many important implications for policy, as it shows that the cognitive skills literacy, numeracy and problem solving are a more general, industry- and task-independent set of skills which strongly relate to labour productivity and to integration into GVCs in all industries, irrespective of the characteristics of each industry. Thus, to increase the productivity and internationalisation of industries it is crucial for governments to provide workers early in life with a good basic endowment of these three cognitive skills through the education system.

Second, the task-based skills analysed also show a significant relationship, albeit of smaller magnitude, with productivity and international forward integration, when controlling for the characteristics of each industry. This suggests that the task-based skills are more industry and occupation specific than the three assessed cognitive skills considered. ICT skills, Management and Communication skills and Readiness to Learn in particular show a significant positive correlation with productivity and forward integration into GVCs, for all industries. Hence, to increase the productivity and forward integration of industries into GVCs, workers might need to be endowed with (more) ICT and Managing and Communication skills as well as greater readiness to learn.

Third, the results indicate that the specialisation of industries in specific tasks positively relates to productivity and forward integration into GVCs. Policies designed to foster the structural transformation of economies should include actions aimed to provide the skills necessary to carry out those specific tasks. Also, enhanced coordination and alignment of industrial and trade policies with education and skills policies seems to be necessary to avoid counteracting policies and arising inefficiencies. As educational institutions and settings and their effects on countries' skill endowments and on human behaviour are generally more persistent than other institutions, it is key to carefully design education and skills policies in the long run, and to align them to the other policies affecting industry structure and performance and specialisation in international trade.

Fourth, understanding the effects of policies on the international integration of industries into GVCs requires bearing in mind that services sectors might export a much higher share of their value added through indirect links, i.e. by supplying domestic manufacturing sectors with intermediate inputs, than through direct exports. The results showed here suggest that it is not sufficient to just include the services sectors and the value added embedded in their exports from the OECD TiVA database in the analysis. Only by accounting for the domestic value added embedded in foreign final demand, one takes the indirect exporting links of services into account and finds that services that specialise in Marketing and Accounting or Management and Communication tasks (and thus require the corresponding skills), *ceteris paribus*, show a higher forward integration into GVCs than services that do not particularly specialise in those tasks. Hence, policies aiming to provide workers with the necessary skills for the internationalisation of the economy need to also focus their attention on the skill requirements of the services sectors. These sectors, traditionally labelled as “non-tradable”, are often an important supplier of intermediate inputs to the directly exporting manufacturing industries.

Finally, the data for the constructed new task-based skill indicators will be made available for policy makers to support them in analysing which type of skills are required in industries and occupations within their countries and to inform their educational policies accordingly.

APPENDIX A

Table A1: Robustness checks for the exploratory factor analysis

Item	Baseline	Polychoric Correlations	Country - Sub samples					
			PIAAC First Round	OECD	USA	Canada	France	Germany
g_q05d	Skill use work - ICT - Internet - How often - Conduct transactions	ICT	ICT	ICT	Drop.	Drop.	Drop.	ICT
g_q05e	Skill use work - ICT - Computer - How often - Spreadsheets	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q05g	Skill use work - ICT - Computer - How often - Programming language	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q01b	Skill use work - Literacy - Read letters memos or mails	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q02a	Skill use work - Literacy - Write letters memos or mails	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q05a	Skill use work - ICT - Internet - How often - For mail	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q05c	Skill use work - ICT - Internet - How often - Work related info	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q05f	Skill use work - ICT - Computer - How often - Word	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q05h	Skill use work - ICT - Computer - How often - Real-time discussions	ICT	ICT	ICT	ICT	ICT	ICT	ICT
g_q06	Skill use work - ICT - Computer - Level of computer use	ICT	ICT	ICT	ICT	ICT	ICT	ICT
f_q06b	Skill use work - How often - Working physically for long	ICT	ICT	ICT	ICT	ICT	New F.	ICT
i_q04j	About yourself - Learning strategies - Get to the bottom of difficult things	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.
i_q04b	About yourself - Learning strategies - Relate new ideas into real life	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.
i_q04d	About yourself - Learning strategies - Like learning new things	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.
i_q04h	About yourself - Learning strategies - Attribute something new	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	Drop.	R. to L.
i_q04l	About yourself - Learning strategies - Figure out how different ideas fit together	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.
i_q04m	About yourself - Learning strategies - Looking for additional info	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.	R. to L.
f_q04b	Skill use work - How often - Negotiating with people	M. & C.	Drop.	Drop.	M. & C.	M. & C.	M. & C.	Drop.
f_q03b	Skill use work - How often - Planning others activities	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.
f_q02b	Skill use work - How often - Teaching people	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.
f_q02e	Skill use work - How often - Advising people	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	New F.
f_q04a	Skill use work - How often - Influencing people	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	M. & C.	Drop.
d_q11a	Current work - Work flexibility - Sequence of tasks	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.
d_q11b	Current work - Work flexibility - How to do the work	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.

d_q11c	Current work - Work flexibility - Speed of work	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.	S.-O.
d_q11d	Current work - Work flexibility - Working hours	S.-O.	S.-O.	S.-O.	S.-O.	Drop.	Drop.	S.-O.	Drop.
g_q01g	Skill use work - Literacy - Read financial statements	M & A	M & A	M & A	M & A	M & A	M & A	M & A	Drop.
g_q03b	Skill use work - Numeracy - How often - Calculating costs or budgets	M & A	M & A	M & A	M & A	M & A	M & A	M & A	Drop.
g_q03d	Skill use work - Numeracy - How often - Use a calculator	M & A	M & A	M & A	M & A	Drop.	M & A	Drop.	Drop.
f_q02d	Skill use work - How often - Selling	M & A	M & A	M & A	M & A	M & A	M & A	M & A	New F.
g_q03f	Skill use work - Numeracy - How often - Prepare charts graphs or tables	STEM	Drop.	STEM	STEM	Drop.	Drop.	Drop.	Drop.
g_q03g	Skill use work - Numeracy - How often - Use simple algebra or formulas	STEM	STEM	STEM	STEM	STEM	STEM	ICT	New F.
g_q03h	Skill use work - Numeracy - How often - Use advanced math or statistics	STEM	STEM	STEM	STEM	STEM	STEM	Drop.	Drop.
g_q01d	Skill use work - Literacy - Read professional journals or publications	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q01f	Skill use work - Literacy - Read manuals or reference materials	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q02c	Skill use work - Literacy - Write reports	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q01h	Skill use work - Literacy - Read diagrams maps or schematics	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q01a	Skill use work - Literacy - Read directions or instructions	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q01c	Skill use work - Literacy - Read newspapers or magazines	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q01e	Skill use work - Literacy - Read books	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q02b	Skill use work - Literacy - Write articles	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q02d	Skill use work - Literacy - Fill in forms	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
g_q03c	Skill use work - Numeracy - How often - Use or calculate fractions or percentage	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	New F.
f_q05a	Skill use work - Problem solving - Simple problems	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q05b	Skill use work - Problem solving - Complex problems	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q03a	Skill use work - How often - Planning own activities	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q03c	Skill use work - How often - Organising own time	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	S.-O.	S.-O.
f_q01b	Skill use work - Time cooperating with co-workers	Drop.	M. & C.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q02a	Skill use work - How often - Sharing work-related info	Drop.	M. & C.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q02c	Skill use work - How often - Presentations	Drop.	M. & C.	M. & C.	Drop.	Drop.	M. & C.	M. & C.	M. & C.
d_q08	Current work - Managing other employees	Drop.	M. & C.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
i_q07a	About yourself - Social trust - Trust only few people	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
i_q07b	About yourself - Social trust - Other people take advantage of you	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.
f_q06c	Skill use work - How often - Using hands or fingers	Drop.	Drop.	Drop.	Drop.	Drop.	Drop.	New F.	Drop.

Source: Authors' own compilation.

Note: Table A5 shows a set of robustness checks for the allocation of items to the skill indicators. Column 1 shows the allocation of items to factors for the baseline specification of the exploratory factor analysis described in the text and the full set of 31 PIAAC countries (round 1 and round 2 of PIAAC). Column 2 shows the results for using polychoric rank correlations to compute the correlation matrix between the 57 PIAAC items instead of pairwise correlations assuming interval scales for the items (as in the baseline). Columns 3 until 8 apply the exploratory factor analysis to alternative sets of countries (PIAAC round 1, OECD) as well as a selection of single countries (USA, Canada, France and Germany). The Table shows the allocation of items (in the rows) to skill indicators (or whether the items are dropped by the algorithm) for each specification in the column. The abbreviations in the table correspond to the six skill indicators (ICT - ICT skills, R. to L. - Readiness to Learn, M. & C. - Management and Communication Skills, S. - O. - Self-Organization Skills, M & A - Marketing and Accounting Skills, STEM - STEM Skills). "Drop." means the item is dropped by the algorithm and "New F." means that the item is allocated to a new factor that has emerged.

Table A2: Final result of the exploratory factor analysis – Loadings of items on the six extracted factors

Item name	Item label	ICT skills	Readiness to Learn	Management and Communication	Self-Organization	Marketing and Accounting skills	STEM skills
g_q05d	ICT - Internet - How often - Conduct transactions	0.592	0.023	-0.025	0.022	0.318	-0.032
g_q05e	ICT - Computer - How often - Spreadsheets	0.776	-0.015	-0.039	-0.011	0.076	0.182
g_q05g	ICT - Computer - How often - Programming language	0.600	0.026	-0.047	-0.001	-0.054	0.167
g_q01b	Literacy - Read letters memos or mails	0.759	0.008	0.153	0.027	0.030	-0.070
g_q02a	Literacy - Write letters memos or mails	0.767	0.000	0.122	0.041	0.023	-0.028
g_q05a	ICT - Internet - How often - For mail	0.954	0.002	0.044	0.012	0.010	-0.085
g_q05c	ICT - Internet - How often - Work related info	0.881	0.031	0.054	0.008	0.032	-0.041
g_q05f	ICT - Computer - How often - Word	0.887	0.016	0.040	0.001	-0.030	0.030
g_q05h	ICT - Computer - How often - Real-time discussions	0.620	0.040	0.032	0.010	0.018	0.092
g_q06	ICT - Computer - Level of computer use	0.890	0.032	-0.025	0.009	-0.034	0.057
f_q06b	How often - Working physically for long periods	-0.546	0.011	0.117	-0.033	0.029	-0.031
i_q04j	About yourself - Learning strategies - Get to the bottom of difficult things	-0.006	0.731	0.004	0.004	0.002	0.023
i_q04b	About yourself - Learning strategies - Relate new ideas into real life	0.066	0.575	0.041	0.028	0.017	0.017
i_q04d	About yourself - Learning strategies - Like learning new things	0.037	0.718	0.012	0.010	-0.003	-0.030
i_q04h	About yourself - Learning strategies - Attribute something new	0.033	0.697	0.021	0.012	-0.006	-0.001
i_q04l	About yourself - Learning strategies - Figure out how different ideas fit together	-0.008	0.761	0.016	-0.004	0.010	0.017
i_q04m	About yourself - Learning strategies - Looking for additional info	0.060	0.670	-0.022	0.002	0.000	0.004
f_q04b	Skill use work - how often - negotiating with people	0.120	0.016	0.486	0.037	0.276	0.010

f_q03b	Skill use work - How often - Planning others activities	0.071	-0.008	0.541	0.071	-0.021	0.141
f_q02b	Skill use work - How often - Teaching people	0.123	0.039	0.556	-0.004	-0.164	0.127
f_q02e	Skill use work - How often - Advising people	0.147	0.043	0.564	-0.011	0.123	-0.042
f_q04a	Skill use work - How often - Influencing people	0.119	0.038	0.636	0.017	0.138	-0.031
d_q11a	Current work - Work flexibility - Sequence of tasks	0.085	0.002	0.021	0.749	0.020	-0.003
d_q11b	Current work - Work flexibility - How to do the work	0.031	0.018	0.056	0.791	-0.046	0.007
d_q11c	Current work - Work flexibility - Speed of work	-0.017	0.015	-0.018	0.728	0.013	-0.003
d_q11d	Current work - Work flexibility - Working hours	0.068	0.006	-0.038	0.515	0.147	0.006
g_q01g	Skill use work - Literacy - Read financial statements	0.213	-0.003	-0.025	0.046	0.592	0.024
g_q03b	Skill use work - Numeracy - How often - Calculating costs or budgets	0.044	0.018	0.027	0.013	0.705	0.101
g_q03d	Skill use work - Numeracy - How often - Use a calculator	0.211	-0.026	0.010	-0.012	0.509	0.269
f_q02d	Skill use work - How often - Selling products or services	-0.101	0.012	0.204	0.000	0.589	-0.126
g_q03f	Skill use work - Numeracy - How often - Prepare charts graphs or tables	0.293	0.005	0.083	0.007	0.024	0.508
g_q03g	Skill use work - Numeracy - How often - Use simple algebra or formulas	0.064	0.024	0.017	-0.001	0.186	0.548
g_q03h	Skill use work - Numeracy - How often - Use advanced math or statistics	0.051	0.034	0.005	0.017	-0.002	0.533

Source: Authors' own compilation.

Table A3: Loadings of items excluded by the algorithm of the exploratory factor analysis

Item name	Item label	ICT skills	Readiness to Learn	Management & Communication	Self-Organisation	Marketing & Accounting skills	STEM skills
Items excluded due to low loadings							
g_q01a	Skill use work - Literacy - Read directions or instructions	0.203	0.357	0.157	0.045	-0.164	0.034
g_q01c	Skill use work - Literacy - Read newspapers or magazines	0.405	0.246	0.131	-0.004	0.106	-0.045
f_q05a	Skill use work - Problem solving - Simple problems	0.118	0.415	0.032	0.107	-0.013	0.075
f_q05b	Skill use work - Problem solving - Complex problems	0.217	0.348	0.157	0.061	0.021	0.041
f_q03c	Skill use work - How often - Organising own time	0.068	0.266	0.033	0.006	0.424	0.058
f_q01b	Skill use work - Time cooperating with co-workers	-0.093	0.401	-0.089	0.047	-0.183	0.027
f_q02c	Skill use work - how often - presentations	0.143	0.436	0.164	-0.001	0.079	-0.170
d_q08	Current work - Managing other employees	0.073	0.373	0.093	-0.073	0.105	0.057
i_q08	About yourself - Health - State	0.109	0.036	-0.060	0.178	0.018	-0.005
g_q01h	Skill use work - Literacy - Read diagrams maps or schematics	0.153	0.013	0.146	0.424	0.027	-0.001
f_q02a	Skill use work - How often - Sharing work-related info	0.138	0.028	0.383	0.088	-0.132	-0.126
Items excluded due to double loadings							
g_q03c	Skill use work - Numeracy - How often - Use or calculate fractions or percentage	0.180	0.016	0.405	0.030	0.023	0.513
Items excluded due to low and double loadings							
g_q01d	Skill use work - Literacy - Read professional journals or publications	0.344	0.257	0.237	0.042	0.101	-0.093
g_q01f	Skill use work - Literacy - Read manuals or reference materials	0.212	0.330	0.279	0.035	-0.098	-0.028
g_q02c	Skill use work - Literacy - Write reports	0.237	0.283	0.226	-0.011	-0.050	-0.020
g_q01e	Skill use work - Literacy - Read books	0.142	0.249	0.245	0.016	0.038	-0.215

g_q02b	Skill use work - Literacy - Write articles	0.193	0.108	0.140	0.006	0.087	-0.092
g_q02d	Skill use work - Literacy - Fill in forms	0.248	0.255	0.143	-0.021	-0.128	0.150
f_q03a	Skill use work - How often - Planning own activities	0.040	0.331	0.032	0.011	0.411	0.031
i_q07a	About yourself - Social trust - Trust only few people	0.196	0.051	-0.036	-0.014	0.138	-0.192
i_q07b	About yourself - Social trust - Other people take advantage of you	0.243	0.035	-0.057	-0.064	0.173	-0.207
i_q05f	About yourself - Cultural engagement - Voluntary work for non-profit organisation	0.082	0.092	0.024	0.093	0.081	-0.062
i_q06a	About yourself - Political efficacy - No influence on the government	0.110	0.043	-0.008	0.097	0.066	-0.066
f_q06c	Skill use work - How often - Using hands or fingers	-0.253	0.175	0.042	0.089	-0.133	0.077

Source: Authors' own compilation.

Table A4: Eigenvalues of Factors

Factor	Eigenvalue	Difference
Factor1	14.66871	11.91134
Factor2	2.75737	0.79111
Factor3	1.96626	0.14929
Factor4	1.81697	0.16324
Factor5	1.65373	0.59585
Factor6	1.05787	0.10354
Factor7	0.95433	0.20409
Factor8	0.75024	0.07409
Factor9	0.67615	0.10218
Factor10	0.57397	0.12962

Source: Authors' own compilation.

Table A5: Variance explained by factors

Factor	Variance	Proportion
Factor1	12.24724	0.4813
Factor2	7.48366	0.2941
Factor3	5.57339	0.219
Factor4	4.96141	0.195
Factor5	4.93177	0.1938
Factor6	2.89708	0.1138

Source: Authors' own compilation.

Table A6: Correlations between skill indicators and labour productivity at the country-industry level (excluding industry fixed effects)

Panel A: Log of the value added per employee	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.054***	-0.07**	0.045***	0.036***	0.044***	0.049***	-0.04
Numeracy	0.066***	-0.062**	0.055***	0.04***	0.052***	0.064***	-0.015
Problem solving	0.062***	-0.006	0.047***	0.043***	0.063***	0.062***	0.01
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.017***	-0.02***	0.005***	0.007***	0.013***	0.015***	-0.008
STEM	0.037***	0.048***	0.018***	0.028***	0.017***	0.038***	-0.004
Marketing/Accounting	0.01***	-0.024	0.003*	0.011***	0.005*	0.011***	-0.033**
Managing/communication	0.018***	-0.011	0.008**	0.014***	0.012***	0.018***	-0.01
Self-organisation	-0.006	-0.018	-0.003	-0.001	-0.009**	-0.009*	-0.028*
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.015**	-0.031**	0.01*	0.01**	0.004	0.013*	-0.028**

Panel B: Log of output in USD per employee	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.022	-0.109**	0.012	0.023**	0.015	0.009	-0.104**
Numeracy	0.065***	-0.093**	0.049***	0.045***	0.049***	0.055***	-0.052
Problem solving	0.038**	-0.006	0.028*	0.025	0.048**	0.038**	0.003
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.004	0.004	-0.002	-0.002	0.015*	0.006	0.009
STEM	0.051***	0.092***	0.023***	0.025**	0.026***	0.036***	0.044**
Marketing/Accounting	-0.01*	-0.043**	-0.01***	-0.002	-0.008*	-0.009*	-0.036*
Managing/communication	-0.008	0.028	-0.008	-0.006	0	-0.007	0.027
Self-organisation	-0.041***	0.023	-0.026***	-0.025***	-0.034***	-0.044***	-0.021
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	-0.01	-0.023	-0.005	-0.009	-0.011	-0.011	-0.025

Source: Authors' own compilation.

Note: The dependent variable is the log of labour productivity measured as value added per employee (Panel A) and as output in USD per employee. All specifications are estimated using OLS and include dummies for countries as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure). Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one single skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits the 25th and 75th percentiles are considered, as the 10th and 90th percentiles are uninformative due to scarce variation). The heading "Combined specifications" contains specifications including both the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A7: Correlations between skills and exports (in gross and value added terms) and forward linkages, at the bilateral country-industry level (excluding industry fixed effects)

Panel A: Log of Gross Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.091***	0.092***	0.085***	0.027***	0.134***	0.115***	0.168***
Numeracy	0.06***	0.082***	0.058***	0.004	0.09***	0.086***	0.143***
Problem solving	0.161***	0.263***	0.132***	0.073***	0.231***	0.174***	0.313***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.001	0.111***	0.011***	-0.022***	0.05***	0.033***	0.139***
STEM	0.009***	0.139***	-0.012***	-0.02***	0.015***	-0.073***	0.234***
Marketing/Accounting	-0.032***	0.035***	-0.018***	-0.02***	-0.025***	-0.035***	0.064***
Managing/communication	-0.041***	0.218***	-0.026***	-0.054***	0.002	-0.038***	0.214***
Self-organisation	-0.103***	0.118***	-0.072***	-0.071***	-0.072***	-0.101***	0.014
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	-0.002	0.069***	-0.003	-0.006**	0.004	0.001	0.069***

Panel B: Log of Value Added Embedded in Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.104***	0.09***	0.098***	0.034***	0.142***	0.129***	0.175***
Numeracy	0.065***	0.078***	0.065***	0.008*	0.091***	0.091***	0.142***
Problem solving	0.17***	0.256***	0.138***	0.08***	0.234***	0.183***	0.308***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.007***	0.097***	0.013***	-0.018***	0.049***	0.037***	0.128***
STEM	0.007**	0.121***	-0.011***	-0.014***	0.013***	-0.065***	0.207***
Marketing/Accounting	-0.021***	0.047***	-0.012***	-0.012***	-0.018***	-0.024***	0.067***
Managing/communication	-0.03***	0.199***	-0.019***	-0.046***	0.006***	-0.028***	0.196***
Self-organisation	-0.089***	0.104***	-0.062***	-0.061***	-0.062***	-0.086***	0.015*
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.006*	0.06***	0.003	0.001	0.008***	0.009**	0.063***

Panel C: Log of Value Added Embedded in Foreign Final demand	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.077***	-0.058***	0.071***	0.041***	0.073***	0.077***	-0.004
Numeracy	0.069***	-0.051***	0.063***	0.036***	0.056***	0.069***	0
Problem solving	0.106***	0.029***	0.085***	0.067***	0.118***	0.109***	0.062***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	0.017***	0.007***	0.01***	0	0.025***	0.024***	0.027***
STEM	0.026***	0.067***	0.009***	0.015***	0.018***	0.005***	0.06***
Marketing/Accounting	0.018***	0.007*	0.011***	0.02***	0.005***	0.018***	-0.005
Managing/communication	0.003***	0.049***	0	-0.004***	0.01***	0.004***	0.049***
Self-organisation	-0.024***	0.032***	-0.016***	-0.016***	-0.018***	-0.023***	0.009**
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	0.01***	-0.007**	0.007***	0.01***	0.002	0.01***	-0.005

Source: Authors' own compilation.

Note: The dependent variables are: the log of bilateral gross exports (Panel A), the log of bilateral value added exports (Panel B) and the value added embedded in foreign final demand (Panel C) for industry k in home country i and partner country j . All specifications are estimated using OLS and include dummies for home country and for partner country as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure) and bilateral trade cost variables (bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). In Panel A and B, the gravity variables log of production in home country i and industry k as well as log of final demand in partner country j and industry k enter the regression. In Panel C, the independent variable log of value added in home country i and industry k enters the specification. Under the heading “Single specifications”, each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits 25th and 75th percentiles are instead used. Under the heading “Combined specifications”, specifications include the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A8: Correlations between skills and backward linkages at bilateral country-industry level (excluding industry fixed effects)

Panel A: Log of Foreign Value Added in Domestic Final Demand	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	-0.015***	0.017*	-0.02***	-0.01***	0.004	-0.014***	0.007
Numeracy	0.002	0.021***	-0.004	-0.004	0.015***	0.007	0.026***
Problem solving	-0.006	0.08***	-0.002	-0.013***	0.018***	-0.003	0.079***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	-0.018***	0.062***	-0.004***	-0.018***	0.01***	-0.004***	0.058***
STEM	0.001	0.065***	-0.009***	-0.018***	0.004***	-0.04***	0.117***
Marketing/Accounting	-0.029***	0.022***	-0.016***	-0.026***	-0.017***	-0.031***	0.047***
Managing/communication	-0.024***	0.098***	-0.017***	-0.029***	-0.002*	-0.023***	0.096***
Self-organisation	-0.06***	0.051***	-0.041***	-0.042***	-0.043***	-0.062***	-0.012**
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	-0.02***	0.061***	-0.013***	-0.024***	-0.007***	-0.017***	0.057***
Panel B: Log of Foreign Value Added in Exports	Single specifications					Combined specifications	
Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90	Mean	Std
Literacy	0.043***	0.03**	0.033***	0.01***	0.074***	0.053***	0.066***
Numeracy	0.062***	0.027***	0.052***	0.018***	0.078***	0.077***	0.083***
Problem solving	0.081***	0.234***	0.059***	0.02***	0.154***	0.092***	0.262***
Task-based skills	Mean	Std	Median	Perc25	Perc75	Mean	Std
ICT	-0.016***	0.11***	0.001	-0.027***	0.038***	0.014***	0.122***
STEM	0.026***	0.175***	0	-0.033***	0.026***	-0.066***	0.262***
Marketing/Accounting	-0.046***	-0.005	-0.028***	-0.027***	-0.035***	-0.047***	0.031***
Managing/communication	-0.059***	0.194***	-0.037***	-0.061***	-0.01***	-0.057***	0.188***
Self-organisation	-0.108***	0.106***	-0.071***	-0.07***	-0.08***	-0.109***	-0.006
Personality traits	Mean	Std	Median	Perc25	Perc75	Mean	Std
Readiness to learn	-0.039***	0.052***	-0.023***	-0.027***	-0.019***	-0.036***	0.043***

Source: Authors' own compilation.

Note: The dependent variable is the log of foreign value added from partner country j in domestic final demand of industry k in home country i (Panel A) and the log of foreign value added from partner country j in exports of industry k in home country i (Panel B). All specifications are estimated using OLS and include dummies for home country and for partner country as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure) and bilateral trade cost variables (bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). In Panel A, the log of final demand in home country i and industry k enters the regression. In Panel B, the independent variable log of production in home country i and industry k enters the specification. Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one single skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits the 25th and 75th percentile instead of the 10th and 90th are used). Under the heading "Combined specifications", specifications include the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A9: Correlations between mean literacy skills and labour productivity in value added (1) and output terms (2) at a country-industry level

VARIABLES	(1) Log of Value Added per Employee	(2) Log of Output per Employee
Mean of Literacy	0.029** (0.013)	0.039* (0.020)
Skill intensity	0.395 (0.241)	0.624* (0.349)
Log of Capital Intensity	0.177*** (0.053)	0.234*** (0.067)
R&D Expenditure	0.005*** (0.001)	-0.001 (0.001)
Constant	0.425 (0.934)	-0.141 (1.361)
Observations	256	256
R-squared	0.898	0.901
Adjusted R-squared	0.880	0.883

Source: Authors' own compilation.

Note: The dependent variable is the log of labour productivity measured as value added per employee (1) and as output in USD per employee (2). All specifications are estimated using OLS and include dummies for countries and industries as well as the country-industry control variables skill intensity (share of medium and high skilled employees), log of the capital intensity (real net assets per employee) and R&D expenditure (in Billion USD). Country-industry cells with less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the country level (in parenthesis). *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A10: Correlations between literacy skills and the TiVA indicators, bilateral country-industry level

VARIABLES	(1) Log of Gross Exports	(2) Log of Value Added Embedded in Exports	(3) Log of Value Added Embedded in Foreign Final demand	(4) Log of Foreign Value Added in Domestic Final Demand	(5) Log of Foreign Value Added in Exports
Mean of Literacy	0.058*** (0.009)	0.062*** (0.009)	0.007* (0.003)	0.024*** (0.005)	0.072*** (0.006)
Log of Capital Intensity	0.066** (0.028)	0.063** (0.028)	0.107*** (0.008)	0.106*** (0.015)	0.016 (0.013)
R&D Expenditure	0.001 (0.001)	0.004*** (0.001)	0.002*** (0.001)	-0.003*** (0.001)	-0.000 (0.001)
Skill intensity	-0.127 (0.237)	-0.285 (0.237)	-0.091 (0.077)	0.025 (0.166)	-0.380*** (0.141)
Common Border	0.136 (0.144)	0.135 (0.143)	0.195** (0.093)	-0.187 (0.130)	-0.386*** (0.148)
Common official language	0.126 (0.138)	0.134 (0.137)	0.114 (0.094)	0.152 (0.105)	0.033 (0.137)
Common Language between ethnicities in the country	0.187 (0.131)	0.189 (0.131)	0.117 (0.089)	-0.099 (0.105)	-0.108 (0.135)
Ever had colonial links	0.507*** (0.163)	0.504*** (0.162)	0.302*** (0.106)	0.336*** (0.122)	0.386*** (0.123)
Common Colonizer	1.272 (1.206)	1.276 (1.195)	0.900 (1.022)	0.526 (1.193)	0.423 (1.285)
Colonial links after 1945	0.375 (0.249)	0.361 (0.248)	0.252 (0.184)	0.261 (0.220)	0.130 (0.212)
Same Country	0.313 (0.290)	0.295 (0.288)	0.213 (0.184)	-0.101 (0.225)	-0.186 (0.223)
Log of Distance	-1.284*** (0.052)	-1.276*** (0.052)	-0.910*** (0.035)	-1.200*** (0.060)	-1.261*** (0.070)
Log of Production	1.270*** (0.032)	1.205*** (0.031)			1.166*** (0.021)
Log of Final Demand of the Importer	0.243*** (0.024)	0.242*** (0.024)			
Log of Value Added			1.100*** (0.014)		
Log of Final Demand				0.346*** (0.024)	
Constant	-6.992*** (0.848)	-6.626*** (0.835)	-1.518*** (0.443)	8.432*** (0.746)	-4.155*** (0.888)
Observations	14,783	14,746	15,100	15,360	15,359
R-squared	0.802	0.800	0.933	0.884	0.878
Adjusted R-squared	0.800	0.799	0.933	0.883	0.877

Source: Authors' own compilation.

Note: The dependent variable is the log of bilateral gross exports (1), the log of bilateral value added exports (2) and the value added embedded in foreign final demand (3) for industry k in home country i and partner country j . In columns 4 and 5, the dependent variable is the log of foreign value added from partner country j in domestic final demand of industry k in home country i (4) and the log of foreign value added from partner country j in exports of industry k in home country i (5). All specifications are estimated using OLS and include dummies for home country, for partner country and for industries as well as bilateral trade cost variables (log of the bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). The country-industry control variables are skill intensity (share of medium and high skilled employees), log of the capital intensity (real net assets per employee) and R&D expenditure (in Billion USD). In columns 1 and 2, the gravity variables log of production in home country i and industry k as well as log of final demand in partner country j and industry k enter the regression. In column 3, the independent variable log of value added in home country i and industry k enters the specification. In column 4, the log of final demand in home country i and industry k enters the regression, whereas in column 5, the independent variable log of production in home country i and industry k enters the specification. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level (in parenthesis). *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A11: Robustness checks: Correlations between skill indicators and labour productivity (in value added terms) without industry level control variables

Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90
Literacy	0.043***	-0.018	0.044***	0.019**	0.025*
Numeracy	0.043***	-0.013	0.036***	0.019***	0.031***
Problem solving	0.038***	-0.01	0.033***	0.017**	0.018
Task-based skills	Mean	Std	Median	Perc25	Perc75
ICT	0.015***	0	0.005***	0.004*	0.005*
STEM	0.019***	0.016	0.009***	0.011**	0.005*
Marketing/Accounting	0.008*	0.009	0.003	0.002	0.006***
Managing/communication	0.01*	-0.009	0.006*	0.004	0.002
Self-organisation	-0.005	-0.021*	-0.002	-0.001	-0.004
Personality traits	Mean	Std	Median	Perc25	Perc75
Readiness to learn	0.01	-0.01	0.004	0.004	0.001

Source: Authors' own compilation.

Note: The dependent variable is the log of labour productivity measured as value added per employee. All specifications are estimated using OLS and include dummies for countries and industries. Under the heading "Single specifications", each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one single skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits we consider the 25th and 75th percentile, because for some skill indicators there is not much variation of the 10th percentile across country-industries). Under the heading "Combined specifications", specifications include the mean and standard deviation of one skill variable at the same time. Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table A12: Robustness checks: Correlations between skill indicators and exports in value added terms (EXGR_DVA) without industry level control variables (bilateral country-industry level data)

Assessed cognitive skills	Mean	Std	Median	Perc10	Perc90
Literacy	0.026***	0.009	0.024***	0.006*	0.039***
Numeracy	0.025***	-0.01	0.019***	0.012***	0.026***
Problem solving	0.025***	0.006	0.009*	0.02***	0.023***
Task-based skills	Mean	Std	Median	Perc25	Perc75
ICT	0.007***	-0.002	0.004***	0.001	0.001
STEM	0.011***	0.024***	-0.001	0.015***	0.004***
Marketing/Accounting	-0.009***	-0.021***	-0.006***	-0.007***	-0.003**
Managing/communication	-0.002	0.032***	0	-0.01***	0.002
Self-organisation	-0.021***	-0.008	-0.015***	-0.012***	-0.018***
Personality traits	Mean	Std	Median	Perc25	Perc75
Readiness to learn	-0.01***	0.054***	-0.005**	-0.014***	0.006***

Source: Authors' own compilation.

Note: The dependent variable is the log of bilateral value added for industry k in home country i and partner country j . All specifications are estimated using OLS and include dummies for home country, for partner country and for industries as well as country-industry control variables (skill intensity, capital intensity and R&D expenditure) and bilateral trade cost variables (bilateral distance as well as a dummy variable for common coloniser, common language, sharing a common border, having ever had a colonial link, having had colonial ties after 1945 and whether both countries were once the same country). Also, the gravity variables log of production in home country i and industry k as well as log of final demand in partner country j and industry k enter the regression. Each cell corresponds to a single specification, whereby one single moment of the country-industry distribution of one skill indicator enters the regression specification (the mean, standard deviation, median, the 10th percentile and the 90th percentile are considered; for task based skills and personality traits 25th and 75th percentiles are instead used). Country-industry cells having less than 25 observations in PIAAC are excluded to reduce measurement error. Robust standard errors are clustered at the home country - partner country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.

APPENDIX B: A REVIEW OF THE LITERATURE ON THE LINK BETWEEN SKILLS, JOBS AND ECONOMIC PERFORMANCE

Understanding the links between workers' skills and capabilities - performance on the job – and economic performance requires a theoretical underpinning. Two frameworks appear particularly relevant in this respect: the Resource Based View (RBV) of the firm and the High-Performance Work Systems (HPWS) approach. In addition, the economics literature focusing on education and skills provides important insights on the role of individuals' abilities for labour market outcomes.

Thanks to the pioneering work of scholars like James Heckman, individuals' skills have been recognised as fundamental determinants of economic and social success. In turn, formal academic institutions as well as families and firms have been recognised as sources of learning (Heckman, 2000). Cognitive skills involve conscious intellectual effort and include long- and short-term memory, auditory processing, visual processing, processing speed, and logic and reasoning. “Non-cognitive skills”, also known as “soft skills” or personality traits or character qualities, involve the intellect in a more indirect and less conscious fashion than cognitive skills, and relate to individuals' personality, temperament, attitudes, integrity and interpersonal interaction. Examples of studies arguing for the importance of cognitive skills for job performance are Schmidt (2002), Schmidt and Hunter (2004) and Hanushek and Woessmann (2008). Heckman and Rubinstein (2001) emphasise the importance of noncognitive skills in particular. Finally, many analyses stress the importance of both cognitive and non-cognitive skills for occupational attainment and performance on the job (e.g. Heckman et al., 2006; Kautz et al., 2014).

The RBV emphasises the importance of internal firm resources, also and especially human resources (HR), as sources of competitive advantage, thus shifting the emphasis of the strategy literature away from external factors (e.g. industry position). In its original formulation, it posits that strategic resources are heterogeneously distributed across firms and suggests the use of four indicators, i.e. value, rareness, imitability, and substitutability, for the identification of firm resources able to generate sustained competitive advantage (Barney, 1991). The resource-based view of the firm has profoundly influenced the strategic human resource management literature and its exploration of HR's role in supporting business strategy (see Wright et al., 2001, for a discussion).

The High-Performance Work Systems (HPWS) literature emphasises the need for a systematic and integrated approach to the management of human resources so that HR functions are aligned to the achievement of firms' strategies. As human capital becomes more and more central in the quest for sustainable competitive advantages, a skilled and motivated workforce, able to provide the speed and flexibility required by the new global market imperatives, becomes key for organisational performance. Workers are seen as a source of value rather than a cost to be minimised and high-performance work systems able to attract, develop, and retain key HC become significant elements in strategic decision making, especially as command and control organisational structures decline. HPWS are thus held to play a strategic role with respect to supporting the development of core competencies and to enabling an effective strategy implementation. Extremely interesting in this respect are Becker and Huselid's (1998) discussion of HPWS and firm performance; and Shin and Konrad's (2014) analysis of the directions of causality between high-performance work systems and organisational performance.

Surveys also indicate that skills are important from the employers' perspective, with team working being ranked at the top for the very important skills in a Gallup survey (The Gallup Organisation, 2010). Using a revealed preference approach based on employer surveys, Humburg et al. (2013) find that those skills that can enhance graduates' chances to get hired for the job can be ranked as follows: professional

expertise (19.5%), interpersonal skills (19.1%), commercial/entrepreneurial skills (17.6%), innovative / creative skills (16.0%), strategic/organisational skills (14.2%), and general academic skills (13.7%).

In what follows, attention is mostly confined to those parts of the cited literatures aimed at identifying key HR skills and abilities and at understanding the possible mechanisms through which they may lead to superior organisational and economic performance, and, consequently, contribute to firm and industry performance in a globalised world. Relevance for economic outcomes and for policy making, and the possibility to operationalise the analysis on a cross country basis motivate the succinct literature survey proposed. As such, this concise review does not do justice to the breadth and depth of existing contributions.

Cognitive skills

Reading, writing and numerical skills

Broad agreement exists in the fields of industrial organisation, psychology and labour about the fact that general cognitive ability - which is essentially the ability to learn - helps predict both occupational level attained and performance within one's chosen occupation, as well as the ability to benefit from training (e.g. Schmidt, 2002, Schmidt and Hunter, 2004). A subset of cognitive abilities called specific aptitudes, or simply aptitudes, include verbal aptitude, spatial aptitude, and numerical aptitude.³⁶

Many are the studies emphasising the importance of cognitive skills and, more recently, the joint importance of cognitive and non-cognitive skills (discussed later) for job and economic performance. For instance, Hanushek and Woessmann (2008) argue that there is strong evidence that the cognitive skills of the population, rather than school attainment, relate to individual earnings, the distribution of income and more generally economic growth. However, Heckman and Vytlacil (2001) caution that since cognitive ability and schooling are so strongly related it is basically impossible to independently vary these two variables and still be able to estimate their impact separately.

Hoyles et al. (2002) suggest that numeracy and mathematical skills are cognitive abilities that are conducive to business success. They underline that a growing number of jobs require not only numerical skills but also some mathematical literacy, i.e. the ability to apply a range of mathematical concepts integrated with a detailed understanding of the workplace context. In an increasingly competitive and technology-based global economy, mathematical literacy and the use of IT in the workplace get more and more linked. Hoyles et al. (2002) further argue that mathematical skills are always deployed towards certain goals, which they group on five interrelated goals, namely: improving efficiency, dealing with constant change and innovation, informing improvement, remaining competitive, and maintaining operations.

ICT skills

Existing studies in different fields point to the importance of Information and Communication Technologies (ICT) for firm performance, intended as investment in ICT hardware and software as well as ICT related skills.

Management and organisation-related analyses in an RBV context argue that ICT should be considered as an organisational capability and empirically investigate the relationship that exists between ICT capabilities and firm performance. For instance, Bharadwaj (2000) find that firms with high ICT capabilities - intended as ICT infrastructure, ICT-related human resources, and ICT-enabled intangible assets - tend to outperform comparable firms on a number of profit and cost-based performance measures. Santhanam and Hartono (2003) find that firms with higher ICT capabilities are characterised by higher

performance, both contemporaneous and sustained over time, as compared to average industry performance. Tippins and Sohi (2003) further underline that the reason why ICT investment seemingly pays off for some companies but not others depends on organisation learning and on ICT competencies and show organisational learning to play an important role in mediating the effects of ICT competency on firm performance.

Among the economic studies in the field, Dickerson and Green (2004) propose a methodology for the measurement of job skills using survey data on detailed work activities, and use these measures to assess how the labour market value skills and whether the use of skills is growing. They find that in the United Kingdom the utilisation of computing skills, literacy, numeracy, technical know-how, communication skills, planning skills, and problem-solving skills has grown over time. They see that computer skills utilisation grew the fastest and the use of computers became more sophisticated. Also, they investigate whether computer use affected wages and find that both computer skills and high-level communication skills endowments carried positive wage premia. Wage premia and their determinants are also at the centre of MacCrory et al.'s (2015) analysis of skill-biased technical change (SBTC). In particular, they examine how the earnings related to different skills changed over the period 2006-2014 in the United States. They find that different skills indeed command different wage levels (although in a non-linear fashion), and that such wage effects depend on both the actual use of ICT in the occupation and the ICT intensity of the industry. Finally, Bloom et al.'s (2014) analysis based on a recent Census Bureau survey of management practices in the US finds that more structured management practices are highly associated with higher levels of ICT intensity. They find that structured management is strongly correlated with superior performance in terms of productivity and profitability as well as innovation and employment growth, and that management practices vary substantially across establishments.

Personality traits or “non-cognitive skills”

Much of 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), which suggested 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. One of these factors in particular, i.e. conscientiousness, has been found to be consistently predictive of job performance, occupational level and performance in job training programs (see e.g. Barrick and Mount, 1991). It was found that the level of validity of such prediction was higher when conscientiousness is assessed using ratings by others rather than self-report assessments (Schmidt and Hunter, 2004). Conscientiousness is associated to skills as grit, perseverance, delay of gratification, impulse control, achievement striving, ambition, and work ethic. Agreeableness translates into skills as empathy, perspective taking, cooperation, and competitiveness. Emotional stability relates to the locus of control, and to skills as self-evaluation and self-esteem, self-efficacy and optimism (see Kautz et al., 2014, for a discussion).

While psychology and personality studies appeared advanced at the beginning of the new millennium, still in 2001 Heckman and Rubinstein noted that too little was understood about how non-cognitive skills are generated or about their effects. Also they stated that while it was common knowledge outside academic journals that motivation, tenacity, trustworthiness, and perseverance were important for succeeding in life, research in the field was still in its infancy.

Since then much progress has been made, not only to better understand the role of personality traits skills as such, but also and especially to assess whether and to what extent cognitive and personality traits jointly shape labour market outcomes and job performance.

Heckman et al. (2006) find that non-cognitive skills strongly influence schooling decisions and affect wages, given schooling decisions. They argue that schooling, employment, work experience, and choice of occupation are affected by latent non-cognitive and cognitive skills and that gender differences seem to exist in the effects of these skills. Also, they find that for a variety of dimensions of behaviour and for many labour market outcomes, changing non-cognitive skills from the lowest to the highest level has an effect on behaviours which is comparable to or even greater than corresponding changes in cognitive skills. Latent non-cognitive skills seemingly raise wages through their direct effects on productivity, as well as through their indirect effects on schooling and work experience. OECD (2015) reviews a large range of researches finding similar results.

Kautz et al. (2014) argue that, for many outcomes, the predictive power of non-cognitive skills rivals or exceeds that of cognitive skills. In addition, they state that IQ tests and achievement tests are not able to adequately capture non-cognitive skills or personality traits, nor those goals, character, motivations, and preferences that are typically valued not only at school but also in the labour market and in many other domains.

There is no perfect term to refer to these skills. The term "personality traits" suggests the idea that these skills are permanent and can to some extent be inherited; the wording "skills" suggests that these attributes can be to some extent learned. The term "non-cognitive" suggests that these skills do not have a cognitive component. However, many of these skills are a mix of traits that individuals are to some extent born with and of abilities that can to some extent be learnt and improved over the time.

OECD (2015) collects evidence on how policy makers, schools and families can facilitate the development of these skills. The report suggests that promoting strong relationships between educators (e.g. parents, teachers and mentors) and children, mobilising real-life examples and practical experience in existing curricular activities, and emphasising hands-on learning in extracurricular activities represent effective approaches to enhance their sense of responsibility, capacity to work in a team and self-confidence.

Trust

Experts in psychology, sociology, management and economics agree on trust being a hallmark of effective relationships and to affect the extent to which motivation is converted into work group processes and performance. Most of the trust-related research initially positioned trust as a variable having a direct effect on work group processes and performance, arguing that increasing (decreasing) levels of trust should lead to superior (inferior) group processes (e.g. higher (lower) levels of cooperation) and higher (lower) performance. More recently, trust has also been looked at as a construct that indirectly influences group performance, through channelling group member's energy toward reaching alternative goals (see e.g. Dirks, 1999).

Mayer and Gavin (2005) investigate how employees' trust in plant managers and top management team relates to in-role performance. They find that trust in these two managerial profiles relates to the ability of employees to focus on value-producing activities, i.e. the work that needs to be done, and that this focus in turn relates to performance. Conversely, lack of trust diverts employees' attention from activities contributing to the performance of their organisation. They further argue that different management levels affect employees' ability to focus on the work to be carried out in different ways. Direct managers shape employees' ability to focus their attention as their decisions affect employees' daily life: if employees feel that they need to monitor the managers' actions or to worry about them, this will inevitably distract workers' attention from their daily tasks. Conversely, as the top management and its decisions affects the culture and success of the organisation, including a company's financial position, strategies and policies, a lack of trust in top management likely makes employees spending time and

mental energy speculating about the future and about possible layoffs. Meyer and Gavin (2005) further underline that while their empirical analysis provides evidence about the fact that trust in management can improve organisational performance, when trust cannot be used, performance can be enhanced through using e.g. training and performance incentives, and through a clear system of monitoring and controlling performance.

Colquitt et al (2007), in addition to reaffirming the importance of trust for having employees' full attention devoted to job tasks (rather than, e.g. diverting energy to monitoring), underline that trust allows the development of more effective exchange relationships between workers, which in turn fosters better performance behaviours on the job. Using task performance variables as objective indices of the fulfilment of job duties, as well as supervisory assessments and self-ratings, they find that moderately strong relationships exist between trust and task performance. Trust turns to be vital for effective working relationships, as individuals who are willing to trust others tend to engage in better task performance and to commit fewer counterproductive behaviours.

Conscientiousness and job engagement

While the relationships between personality measures and job performance may to some extent vary depending on the which of the big five constructs is considered, both theoretical and empirical evidence agree on conscientiousness, and the consequent engagement into job tasks that it entails, as being positively related to work outcomes (see Schmidt, 2014, for a review).

Engagement can be described as an emotional concept, whereby employees devote their physical, cognitive, and emotional energies to perform on the job. Rich et al. (2010) identify in value congruence, perceived organisational support and core self-evaluations the antecedents of engagement, and argue that engagement represents an investment into role performance which contributes to explain two aspects of job performance: task performance and organisational citizenship behaviour. Engaged individuals work with greater intensity on their tasks, also for longer periods of time; pay more attention to what they do; are more focused on their responsibilities; and are more emotionally connected to the tasks that constitute their role, and these behaviours directly enhance performance. In addition, engagement leads to less formal behaviours such as helpfulness, conscientiousness and civic virtue, which contribute indirectly to the functioning and performance of organisations, by means of fostering social and psychological environments conducive to work accomplishment.

Barrick et al. (2013) even propose a theory of purposeful work behaviour which builds, among others, on the big five factor model of personality with the aim to explain how personality traits and job characteristics interact and influence work outcomes. They argue that personality traits make people goal oriented and when such motivational forces act jointly with job characteristics, individuals end up in a state called "experienced meaningfulness". This triggers task-specific motivational processes, which in turn positively influence the attainment of work outcomes.

Openness to experience

Openness to experience is one of the dimensions of the big five factors. Yet, openness to experience is difficult to capture and has thus been less covered by the literature than other major personality traits. Several articles have shown that openness to experience encourages workers to undertake training and enables them to better benefit from it (Barrick and Mount, 1991). Matzler et al. (2008) find significant correlations between openness to experience (as well as agreeableness and conscientiousness) and knowledge sharing using data of an internationally operating engineering company.

Evidence on how openness to experience affects work outcomes and firm performance is mixed. Openness to experience appears to be important under specific conditions. For instance, it can be an important skill when workers face unfamiliar environments and when they need to acquire new learning and experience to be successful in their jobs. To test this idea, Bing and Lounsbury (2000) analyse the impact of this skills for employees from the Appalachian region of the U.S. working in traditional Japanese manufacturing companies. They find a positive relationship between openness to experience, beyond both cognitive aptitude and the other four big five factors, and employees' job performance along a number of dimensions including productivity, quality and attendance.

Openness to experience might also be important for relatively complex jobs that involve autonomy, require unconventional thinking and the adoption of new behaviours and ideas in order to achieve a high job performance level. Based on a study of Indian employees in a multinational medical transcription company, Mohan and Mulla (2013) find that openness relates positively to performance in high complexity jobs and negatively to performance in low complexity jobs.

Workers who have acquired their diplomas abroad or who have worked abroad or workers with an immigrant background may be more open to experience than other workers and, more generally, may have acquired some specific skills that are valued by firms, especially if operating in an international environment. Several theoretical articles have looked at the effect of the ethnic and cultural diversity on firm performance, but the link is unclear. On the one hand, ethnic-cultural diversity may affect firm performance negatively because it may hinder potential knowledge transfer among workers due to linguistic and cultural barriers (Lazear, 1999) or because workers distrust workers of other ethnic groups (Alesina and La Ferrara, 2002). On the other hand, cultural diversity brings about variety in skills, experiences, ways in which individuals interpret problems and use their cognitive skills to solve them, and cultures that may lead to innovation, creativity and productivity gains (Alesina and La Ferrara, 2005).

Alesina and La Ferrara, (2005) propose a theoretical framework in which the skills of individuals from different ethnic groups are complementary in the production process for a private good, implying that more diversity translates into increased productivity. However, for these productivity gains to be realised, the production process needs to be sufficiently diversified. A group of individuals with diverse but limited problem-solving skills can even outperform a more homogeneous group of high-skilled problem solvers (Hong and Page, 2004). According to Berliant and Fujita (2008), knowledge creation occurs at its fastest rate when common and differential knowledge is in balance. The process of cooperative knowledge creation reduces the heterogeneity of team members through the accumulation of knowledge in common. In this respect, a perpetual reallocation of members across different teams may be necessary to keep creativity alive.

Quantitative analyses generally find that the link between cultural diversity and economic performance depends on the context. Parrotta et al. (2014) analyse the effects of diversity within firms, measured in terms of the cultural, skill and demographic dimensions on total factor productivity, using a rich matched employer-employee dataset for Denmark. Cultural diversity is represented either by employees' nationalities or by the languages they speak. Their estimates point towards a negative association between ethnic diversity and firm-level productivity. The negative coefficient of ethnic diversity among white-collar workers is lower than the coefficient associated with blue-collar occupations.

Several authors have conversely found a positive link. Trax et al. (2013) use German establishment data to estimate the effect of cultural diversity on total factor productivity. The authors find that productivity spillovers come from the diversification, not from the size of the group of foreign workers. A larger share of foreign employees – either inside the establishment or in the region – does not spur productivity gains while greater diversity of employees across different nationalities does lead to stronger total factor productivity. Using data for the United States, Ottaviano and Peri (2006) ask what is the

economic value of the “diversity” that the foreign born bring to each city. Foreign born are different from US born in their skills and abilities and therefore could be valuable factors in the production of differentiated goods and services. The authors find that diversity has a positive impact of the wages of the natives. The result holds when the authors control for the average schooling of the foreign-born, which they interpret as a sign that foreign born have specific skills.

Cognitive skills/personality traits: skills that combine both aspects

An important point made by Kautz et al. (2014) is that while both cognitive skills and personality traits change and can be changed over the life cycle, this happens through different mechanisms and with different ease at different ages. Also, it is at times difficult to label (a set of) skills as pure cognitive or non-cognitive, as often skills are the results of purposeful learning processes as well as of personal traits and of the combination of different types of skills. Examples are management skills and creative problem solving skills. Also, it has been found that correlations between cognitive ability measures and personality measures are usually low, and correlations between measures of the big five construct are usually moderate. As both cognitive ability and personality are valuable predictors of job performance, and given their relative lack of correlation with each other, combinations of the two are likely to produce superior predictions of job performance (Schmitt, 2014).

In the present work, skills are considered as a continuum, with some skills having mostly a cognitive component, some skills being mostly linked to personality traits, and some skills coming from the interaction and combination of these two components. This latter category, while stemming from attitudes and propensities that some individuals have, can nevertheless be largely shaped and enhanced through (active) learning processes and experience.

Managerial and organisational competencies

More than half a century of psychology, human resources, organisation, management, finance, entrepreneurship, innovation and economics studies have underlined the relevance of different managerial profiles, tasks and abilities for the performance of firms.

The important contributions that the RBV of the firm has made in the field of human resource management (HRM) and its emphasis on people as strategically important to a firm’s success have led to a rapid growth of strategic human resource management studies, and to fostering interaction and convergence of strategy and HRM (see Jay et al., 2001, for a discussion). Among others, these highlight the importance of strategic management abilities for the generation of sustainable competitive advantages (e.g. Hill et al, 2014) and for enhancing competitiveness in global markets (e.g. Hitt et al. 2012). In turn, and given the centrality of human resources for the competitiveness of firms, emphasis is put on the need of suitable human resource management practices to effectively align organisational, group and individuals' objectives with organisations' strategies (see e.g. Lazear and Gibbs, 2014; Buller and McEvoy, 2012). Among the key tasks to be accomplished and the skills needed for an effective HRM and for strategic management more generally the literature suggests those related to: activities and workforce planning; advising and instructing staff; influencing decisions; negotiating; solving problems; and communicating (see Armstrong and Taylor, 2014, for an extensive discussion).

Recent cross-country studies further find that management practices differ substantially not only across firms, but also across countries and industries (e.g. Bloom and Van Reenen, 2010; Bloom et al., 2012), thus warning about generalising results related to specific industries and countries. Also, recent OECD efforts aimed to better define and measure organisational capital find that managers are not the sole to perform managerial tasks affecting the long-term functioning of firms such as developing objectives and strategies, organising, planning, supervising production and managing human resources (Squicciarini and

Le Mouel, 2012; Le Mouel and Squicciarini, 2015). Such findings support the arguments put forward by Caroli and Van Reenen (2001) and von Krogh et al. (2012) about the fact that tasks traditionally carried out by managers have been progressively devolved upon a wide array of non-managerial occupational profiles. This decentralisation of authority and layering of managerial functions in turn suggests that firm-specific managerial skills and abilities should be assessed and compared across a wide array of occupational profiles, and not only with respect to managers.

Creative problem solving

Common sense, theory and evidence all emphasise the importance of problem solving abilities, both individual-specific and group-related ones, as they are conducive to superior individual and organisational performance. The role of problem solving skills and abilities has been investigated in relation to a wide array of policy-relevant issues, including firm performance, creativity, innovation, leadership, management and entrepreneurship.

A part of this vast and diversified literature addresses the role played by problem solving in developing organisational capabilities and improving firm performance. Examples are Nickerson and Zenger (2004), who even propose a knowledge-based theory of the firm centred on problem solving and knowledge formation; and Katila and Ahuja (2002) who investigate the ways in which firms try to find solutions to problems to create new products and highlight the extent to which firms' differ in the depth and scope of their search efforts. Tippman et al. (2013) investigate how individuals, especially middle managers, solve non-routine problems and design new solutions, and how this translates into the development of organisational capabilities.

The literature addressing the problem solving and link is also very rich, both at the individual and the group level. Problem solving attitude and skills are found to be highly and positively correlated with both individual and "organizational creativity" (Woodman et al., 1993), intended as the creation of a valuable, useful new product, service, idea, procedure, or process by individuals working together in an organisation. Consensus also seems to exist about problem solving abilities being directly and indirectly - i.e. through the creativity conduit - related to innovation, and about problem solving ability and creativity being linked to entrepreneurial endeavours' creation and success. Finally, problem solving and creativity have been analysed in relationship to leadership's traits and needs, and found to be a key component of leadership, also managerial leadership.

A few examples of studies supporting these propositions are mentioned here, but they surely do not do justice to the extensive literature that exists in the different domains. Hargadon and Bechky (2006) investigate creative problem solving modes and emphasise that while some creative solutions are the product of individual insights, others are generated through momentary collective processes which are organisation-specific and reflect a qualitative shift in the nature of creative processes. Wang and Horng (2002) find that creative problem solving training has a positive effect on creativity and R&D performance. Reiter-Palmon and Illies (2004) investigate the role of leadership for creativity and argue that creative outcomes cannot be obtained without sufficient support from the organisations and organisational leaders. Hsieh et al. (2007) propose a theory of the entrepreneurial firm and argue that entrepreneurial opportunities are nothing more than valuable problem solution pairings, and that opportunity discovery stems from a deliberate search or recognition over the relevant solution space. Finally, Lee et al. (2004) contribute to that stream of literature looking at creativity and entrepreneurship from a regional viewpoint.

Self-organisational ability and flexibility on the job

Studies investigating the mechanisms through which high performance work systems lead to superior firm performance suggest adaptive capabilities and workers' flexibility to be key (see, e.g. Messersmith and

Guthrie, 2010; Wei and Lau, 2010). As the current knowledge-based global economic paradigm calls for an ever greater ability to adapt to change and absorb shocks, systems and actors need to be able to adapt and remain flexible. This poses a number of management challenges and ultimately entails having a broader perspective on human resource management, especially in emergent organisations (Messersmith and Guthrie, 2010).

Bhattacharya et al. (2005) look at the extent to which the flexibility of employee skills, employee behaviours, and HR practices relate to HR flexibility and to superior firm performance. Results based on perceptual measures of HR flexibility and on accounting measures of firm performance suggest that skill, behaviour, and HR practice flexibility are significantly related to firm financial performance, and that skill flexibility contributes to cost efficiency.

An important stream of the economics literature investigates the factors that contribute to explain the movements of employment across countries along the production chain. Among them, the degree of codifiability and communicability of the tasks carried out by workers, and the way in which the routine-intensity of tasks, i.e. the extent to which tasks are carried out in a codifiable and repetitive way, affect such patterns. Evidence suggests that the routine intensity of occupations is partially decoupled from workers' skills, as there are low-skill tasks that cannot be routinised (e.g. cleaning activities), whereas some high-skill tasks can (e.g. accounting). Also, the degree to which tasks can be routinised correlates positively with the degree of offshorability of tasks, e.g. in the form of shipments from affiliate to the headquarters (Oldenski, 2012); and negatively with employment levels at home, especially of those occupations which are intensive in such tasks (Becker et al., 2013; Autor and Dorn, 2013; Goos et al., 2014).

Recent OECD work (Marcolin et al, 2016) addressing the role of global value chains, workforce skills, ICT, innovation and industry structure in explaining employment levels of routine and non-routine occupations uncovers the existence of complex interactions between the routine content of occupations and skills, technology, industry structure and trade patents. These do not allow for a neat identification of “winners” and “losers” in a GVC context and point to the importance of decoupling the routine content of occupations from the skills of the workforce to better understand labour market outcomes in a GVC context.

Interacting and communicating

A vast strand of the literature has underlined the role of communication and interactions between workers and teamwork on the performance of firms. Cooperation and interaction between employees result in fewer missed signals between employees, and reduce the time wasted carrying out redundant communications, searching for missing information, and waiting to hear from co-workers (Gittell, Seidner, and Wimbush, 2010; Hamilton, Nickerson and Owan, 2003). Teamwork enables to develop complementarities in production among workers, it facilitates gains from specialisation by allowing each worker to accumulate task-specific human capital, and may encourage gains from knowledge transfer of idiosyncratic information that may be valuable to other team members. For these reasons, it is often argued that the knowledge and skills of a group of workers is higher than the sum of their individual knowledge.

For instance, Ichniowski, Shaw and Prennushi (1997) refer to the “connective capital” of firms as the capital emerging from creating teams of experts which can help to solve problems that cannot be solved by a worker's knowledge. According to Collins and Smith (2006), cooperation, together with trust and shared codes and language contribute to the “social climate”, which determines knowledge exchange and combination and, through this channel, to firm performance.

Many empirical articles based on case studies find a link between cooperation within firms and their performance. For instance, using data on a garment plant in the US, Hamilton, Nickerson and Owan (2003)

show that the introduction of team work was associated with an increase in productivity through two channels, a pure team work effect and the fact that the best workers have self-selected into the team. Hence, their result depart from other studies focussing on free-rider problems, which arise when actions taken by team members are not observable, and could make the best workers reject participation in the team. Based on data for 26 steel plants in the US, Ichniowski, Shaw and Prennushi (1997) find a positive link between “connective capital” and firms' efficiency and productivity.

Cooperation and interaction between workers mediate the impact of human resources practices on outcomes. Similarly, human resources practices can encourage team work and facilitate the exchange and combination of ideas and knowledge among employees. For instance, Collins and Smith (2006) examine how commitment-based HR practices facilitate the development of firm-wide social climate that encourages the exchange and combination of knowledge among knowledge workers. The authors find that a large part of the effects of HR practices on firms performance come from the effect of these practices on the development of exchange of knowledge in firms.

Physical skills

In contrast with many of the skills discussed above, physical skills tend to be relatively job-specific and to some extent less transferable to other occupations or sectors. Yet, they are crucial for completing several tasks and jobs and for firm performance in a number of sectors (e.g. construction, health and well-being, arts, etc.). Physical skills encompass skills relating to strength, coordination, manual or finger dexterity, and some of them take a long time to be acquired. Overall, physical skills are used in both low-skilled and high-skilled jobs and in very different types of occupations (e.g. repairers, surgeons, sport teachers, musicians, etc.). In high-skilled jobs, they are often used in combination with other skills.

As some of the tasks involving physical skills can be (to some extent) automatised or outsourced to countries with lower labour costs, experts have questioned the role of these skills in the future, especially in developed economies. A relatively shared view is that technology has reduced demand for routine manual skills that can be accomplished following explicit rules (Autor et al., 2003; Goldin and Katz, 2007). When core tasks of these occupations follow precise, well-understood procedures, they can be increasingly codified in computer software and performed by machines. Trying to disentangle the effects of trade and technology on jobs and skills, Autor, Dorn and Hanson (2015) find that computerisation is associated with gains in the share of employment in low-education, manual-task-intensive occupations that demand physical flexibility and adaptability, relative to the employment in middle-skill, routine task-intensive jobs. By contrast, increases in trade exposure reduce overall employment in all categories of occupations and task considered by the authors, including in low-education manual-task-intensive occupations.

Some manual skills are complemented by a given technology or even made more necessary because of technology. Autor (2015) takes the example of a construction worker: the demand for manual skills has changed from being an expert with a shovel to driving an excavator. In addition, Autor (2015) argues that there are many tasks that people understand tacitly and accomplish effortlessly but for which neither computer programmers nor anyone else can enunciate the explicit “rules” or procedures. In terms of physical skills, those that include physical flexibility are difficult to replace by automation. Jobs that require visual and language recognition and in-person interactions are also challenging for automation and outsourcing. These skills are important in jobs such as food preparation and serving jobs, cleaning work, in-person health assistance, jobs in security and protective services. Finally, as the demand for some of the manual task-intensive activities appears to rise with aggregate incomes, demand may increase for these skills. Hence, new technologies and productivity growth in other areas may indirectly raise demand for manual task-intensive occupations, by increasing societal income.

NOTES

1. Forward linkages are measured as the domestic value added embedded in foreign final demand. Backward linkages are captured by foreign value added embedded in domestic final demand as well as foreign value added embedded in exports to third countries. For a more detailed description, please see the section on skills and trade in value added.
2. This paper refers to internal OECD work and can be accessed internally as DSTI/EAS/IND/WPIA(2016)1.
3. As taken from Grundke et al. (2016a).
4. The literature survey in Grundke et al. (2016a) additionally identifies the following skills: trust, conscientiousness and openness to experience (all personality traits) as well as communicating and interaction (a mix between personality traits and cognitive skills) and physical skills.
5. These are 23 countries for the period 2011-2012 (the first round of PIAAC) and 8 countries for the period 2014-2015 (the second round of PIAAC). The results of the exploratory factor analysis are robust to only including the first round countries (Appendix A Table A1).
- ⁶ The OECD Survey of Adult Skills is developed and conducted by the OECD Programme for the International Assessment of Adult Competencies (PIAAC).
- ⁷ The first round of PIAAC includes the following 23 countries: Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Germany, Denmark, Estonia, Finland, France, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation (excluding Moscow), the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), the United States. The second round of PIAAC includes 8 countries, namely: Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey.
8. Due to data availability issues, in an earlier internal OECD version of this paper the authors only used data from the first round of PIAAC (Grundke et al., 2016b; internally accessible as DSTI/EAS/IND/WPIA(2016)3). Robustness checks show that the results of the exploratory factor analysis and the econometric analysis are both robust to only including the first round countries (see Appendix A Table A1). Results are available upon request.
- ⁹ Detailed information on the survey's sample design and the sample size by country can be found in OECD (2016).
10. One exception is question F_Q01b, which is also scaled between 1 and 5 but for which categories are 1 "None of the time", 2 ("Up to a quarter of the time"), 3 ("Up to half of the time"), 4 ("More than half of the time"), 5 ("All the time"). The other exception is question G_Q06, which enquires about the level of computer use in three ordered categories, 1 ("Straightforward"), 2 ("Moderate") and 3 ("Complex"), whereby the categories are with described using concrete descriptions of tasks (see PIAAC Background Questionnaire).
11. Question D-Q08b asks the number of people supervised, with replies scaled between 1 and 5 as follows: 1 ("1-5 people"), 2 ("6-10 people"), 3 ("11-24 people"), 4 ("25-99 people") and 5 ("100 and more people"). The question on trust is formulated in a negative fashion and answers are: 1-strongly agree, 2-Agree, 3-

Neither agree or disagree, 4-Disagree, 5-strongly disagree. 5 thus corresponds to the highest trust-related score and 1 the lowest.

12. When rescaling some of the questions, e.g. on ICT use or managing people, frequency questions have been combined with additional binary information on whether the person has ever carried out the activity (e.g. has used a computer or has managed people). This has been done to reduce the number of missing observations in the respective frequency questions, as otherwise individuals answering no in the binary item would have missing observations in the frequency question. In the rescaled item, a zero value was attributed to individuals responding that they had never done the activity concerned and answers then rescaled using steps of 0.2 in a 0-1 interval.
13. A loading is the correlation of an observed variable with a given factor. Loadings are used in order to determine which observed variables contribute the most to a certain factor.
14. The described analysis is carried out on the pooled set of 31 PIAAC countries using built-in Stata® commands.
15. Senate weights are computed by dividing population weights within one country by the total sum of population weights in that country.
16. Conti et al. (2014) have developed a new type of Bayesian factor analysis that jointly determines the number of factors and the most important parameters of the model using a number of test statistics. The implementation of this procedure is not trivial and there is no official algorithm available yet. However, following the advice of Gabriella Conti on how to proceed, the analysis presented in this paper implements the basic features of the Bayesian factor analysis described in Conti et al. (2014) by means of applying classical factor analysis tools.
17. The Kaiser's rule states that factors should be included in the analysis, if their respective eigenvalue is bigger than 1 (Table A4; Conti et al. 2014). The Scree Test consists in plotting eigenvalues and factors and the general rule for the test is to include factors until the line connecting the dots portrays an elbow (Table A4). Regarding the additional variance explained by subsequent factors, a common rule is to exclude factors that explain less than 10% of the remaining variance in observed variables (Table A5).
18. See Mulaik (2010) for details about factor analysis.
19. Table A1 shows the results of an exploratory factor analysis relying on alternative sets of countries (PIAAC round 1, OECD) or a selection of single countries (USA, Canada, France and Germany). The allocation of items to factors is generally stable. The only major changes happen when applying the analysis to the single countries Germany or France. The Marketing & Accounting index disappears in the German sample and the STEM index disappears for the German and the French sample.
20. The results of these and other robustness checks can be obtained from the authors upon request.
21. The results can be obtained from the authors upon request.
22. The procedure underlying the polychoric correlations assumes that all ordered variables (items) originate from normally distributed latent variables that are continuous. The applied procedure predicts the values for the latent variables and then computes the correlation between the predicted continuous variables.
23. For more details, Table A2 presents the loadings matrix from the final step of the exploratory factor analysis.
24. The analysis relies on all 31 countries surveyed in the first and the second round of PIAAC. The data for the first round of PIAAC corresponds to the year 2011, the data for the second round to the year 2014. As

TiVA data are not available for the years after 2011, the productivity and trade in value added data from the year 2011 are used also for the countries in the second round of PIAAC. Robustness checks show that excluding the second round countries from the analysis leaves regression results basically unchanged, and that the persistency of productivity and trade in value added measures at the country-industry level is very high. This indicates that productivity and trade measures for 2011 might be a reasonable proxy for these same measures in 2014. Results can be obtained from the authors upon request.

25. The TiVA 18 industry aggregation level is chosen to decrease the number of country-industry cells with less than 25 observations in PIAAC, as computing estimates based on less than 25 observations may lead to considerable measurement error. In all regressions, country-industry cells with less than 25 observations in PIAAC are excluded.
26. For some task-based skill indicators the variation across country-industries of the 10th and the 90th percentile is very small. Hence, this analysis uses the 25th and the 75th percentile of the country-industry skill distribution for the task-based skill indicators.
27. www.wiod.org
28. All control variables used in the regressions for productivity and trade in value added are for the year 2011. The only exception is industry skill intensity from the WIOD database, which was only available for the year 2009 (not for later years).
29. Moreover, increasing the extent of Self-Organisation within an industry might on average even proxy for a decrease in the size of firms and, thus, lead to a negative effect on overall productivity measured in output terms (Panel B).
30. For some task-based skill indicators the variation across country-industries of the 10th and the 90th percentile is very small. Hence, this analysis uses the 25th and the 75th percentile of the country-industry skill distribution for the task-based skill indicators.
31. <http://www.cepii.fr/>
32. In robustness checks, additional dummy variables controlling for all omitted aggregated sector characteristics for the home and the partner country (18 industries are aggregated into the three sectors resource extraction, manufacturing and utilities as well as services) are added and results do not change. In another robustness check, bilateral dummies are included for each home and partner country pair and the presented results hold. These results can be obtained from the authors upon request.
33. The number of observations for the trade regressions without industry control variables depends on the coverage of the dependent variable and is 27317 for gross exports, 27216 for value added export, 28299 for domestic value added in foreign final demand, 28799 for foreign value added in domestic final demand and 28714 for foreign value added in exports. Including the industry control variables, the number of observation is 14783 (gross exports), 14746 (value added export), 15100 (domestic value added in foreign final demand), 15360 (foreign value added in domestic final demand) and 15359 (foreign value added in exports). Observation numbers do not change across skill indicators or moments of the distribution, except for the assessed skill problem solving which is not available for Italy, France and Spain.
34. Excluding the industry control variables reduces the R-square for the productivity and trade regressions by merely 0.02 points. The R-squares for the different specifications are very similar across different skill indicators and distributional moments and only differ between dependent variables (Tables A9 and A10).
35. To approach the issue of reversed causality, it was tested whether past values of economic performance (i.e. productivity and trade in value added indicators in the year 2000, 2005, 2008 and 2009) are correlated with moments of the industry skill distribution in 2011 (by using the past values of the dependent variables instead the ones for the year 2011). If causality runs from skill supply to industry performance, one should not see any effect of industry skill supply in the year 2011 on past industry performance. However, the results are very similar to the regressions using industry performance in 2011, i.e. a strong and significant

positive correlations of skill supply in 2011 on past industry performance measures. This can have two explanations. First, causality indeed runs from industry performance to industry level skill supply. Second, country-industry level performance and trade flows are highly persistent and one cannot answer the question of causality using cross sectional data. Regressions including lagged dependent variables show that labour productivity and trade flows are highly persistent at the country-industry level, which provides evidence for the second explanation.

36. Numerical problem solving, which is different from problem solving on the job, is also considered a cognitive ability by the literature (see e.g. Schmidt, 2002).

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