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MOVING BETWEEN JOBS

AN ANALYSIS OF OCCUPATION DISTANCES AND SKILL NEEDS

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Foreword

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Abstract

This work sheds light on the quantity and type of training needed to facilitate job-to-job transitions. It aims to inform the design of well-targeted and cost-effective training policies facilitating workers' mobility on the labour market, smoothing transition costs, and fostering (re)employment and well-being. It is motivated by evidence about digitalisation changing the demand for jobs and the task content of occupations: as the digital transformation unfolds, workers may need to be increasingly flexible, to adapt to the performance of new or different tasks, and to be more mobile across occupations.

The analysis is performed at the occupation level on data from the OECD Survey of Adult Skills (PIAAC) for 31 countries. Applying the novel approach of Nedelkoska et al. (2015) on 127 groups of occupations, it assesses the distances that exist between occupations, in terms of cognitive skills and of skills as they emerge from the tasks that workers perform on the job. The resulting "skill shortage" and "skill excess" measures are then used to estimate the training efforts required for workers to move from one occupation to the other and to adapt to the skills requirements of the destination job.

Results suggest that skill distances in terms of cognitive skills are higher among low skilled occupations, or from mid-skilled to high-skilled occupations, than among higher-skilled occupations. Conversely, distances in terms of task-related skills are higher within high-skilled occupations than low-skilled ones, in particular for moves from professionals to managers or within the group of professionals. These results call for policies aimed at developing general cognitive skills complemented by task-related skills for workers in low-skilled occupations, and on-the-job training options for workers in high-skilled occupations.

Executive Summary

Digitalisation is changing the demand for jobs, the task content of occupations and, relatedly, the skills needed to perform them. Such a transformation requires workers to be more flexible and to adapt to the performance of new or different tasks, and may lead to more labour mobility across occupations, especially when "old" jobs disappear. A better understanding of the costs and the opportunities that (re)training and/or up-skilling may have to help workers move within and across occupations thus becomes key for the design of well-targeted and cost-effective training policies aimed at smoothing job-to-job transitions, and at fostering (re)employment and well-being.

This study contributes evidence in support of such policies, by means of assessing the quantity and type of training needed to facilitate job-to-job transitions. The analysis is performed at the occupation level on data from the OECD Survey of Adult Skills (PIAAC) for 31 countries.

Applying the novel approach of Nedelkoska et al. (2015) on 127 groups of occupations, skills' distances are measured in terms of cognitive skills, i.e. literacy and numeracy, and of skills as they emerge from the tasks that workers perform on the job (namely: ICT skills, management and communication skills, accounting and selling skills, advanced numeracy skills and self-organisation skills, as in Grundke et al., 2017). The resulting "skill shortage" and "skill excess" measures are then used to estimate the training efforts required for workers to move from one occupation to the other and to adapt to the skills requirements of the destination job.

Key findings of the analysis are:

- Skill distances in terms of cognitive skills are found to be higher among low skilled occupations or from mid-skilled to high-skilled occupations than among higher skilled occupations. These results call for policies aimed at developing general cognitive skills complemented by task-related skills for workers in low-skilled occupations.
- Occupational moves within the higher skilled occupations, in particular from professionals to managers or within the group of professionals, conversely show that skill distances are large when it comes to task-based skills and relatively small for cognitive skills, thus suggesting the need for on-the-job or other types of training for these occupational moves.
- In terms of task-related skills, moves to the upper group of occupations require workers to acquire specific mix of skills which depend on the occupation of origin. For instance, to reach managerial positions, professionals would need to acquire higher accounting and selling and communicating and managing skills. Conversely service workers would mainly need to increase their ICT skills to move to clerical support occupations.
- Being ready to learn seems important for some of these transitions.

Follow up analysis will estimate the training investment, in terms of monetary expenditures, needed to help workers move between occupations, and investigate whether (re)training costs differ depending on workers' age. It will further try and identify possible labour market trajectories helping workers move away from occupations at risk of automation, that minimise education and training costs as well as the possible human capital losses triggered by moves to occupations for which workers are over-skilled.

MOVING BETWEEN JOBS: AN ANALYSIS OF OCCUPATION DISTANCES AND SKILL NEEDS

Introduction[1]

The ongoing digitalisation of economies and societies is reshaping the way people work and the skills needed on the job. Many workers now use several information and communication technologies (ICT) on their job, like computers, touchscreens and mobile digital devices to perform old and new tasks; others see the nature and content of their occupation change, as machines take over part of their tasks or displace their jobs entirely. Digitalisation can both create and destruct jobs, depending on the specific form it takes: while automation may make some jobs redundant, access to online markets may create new jobs. Also the new technological developments occurring in the digital space may enhance participation in the labour market, thanks to the flexibility that they entail, and may enable the creation of new businesses and business models, such as those based on digital platforms.

Of the many facets that the digital transformation may take, in recent years policy makers have been very much concerned with the job losses linked to automation. Especially in manufacturing industries, the digital transformation has in fact led to the substitution of many workers carrying out repetitive and codifiable tasks, the so called “routine” tasks (see Marcolin et al., 2016a). As digital technologies develop and get adopted in different sectors, fears about further tasks being automated also grow. In such a fast-changing environment where digitalisation alters the task-content of jobs (Autor et al., 2003; Acemoglu and Restrepo, 2016), workers will have to adapt to the continuously evolving demand for skills and may need to become more mobile. This may in turn require workers to possess or acquire different skills, both to be able to meet new requirements on their current jobs and to transit smoothly to other occupations, when necessary.

While workers’ mobility across occupations appears to have intensified in the last decades in some countries (see e.g. Kopczuk et al., 2010, for the United States; Lalé, 2009, for France), substantial heterogeneity nevertheless remains across OECD economies, in terms of mobility and workers’ turnover in general (Pries and Rogerson, 2005; Kambourov and Manovskii, 2008; Carillo-Tudela et al., 2016). To the extent that the specific human capital needed for different jobs varies, job to job transitions - in the form of either reallocation or displacement within and across firms and sectors - will engender costs and require retraining. Also, the disruptions brought about by the digital transformation in terms of skill requirements, coupled with higher job mobility, may entail the need for workers to (re)adapt and upgrade their skills while trying to minimise potential human capital losses, and to have to do so several times over their working life.

The challenge for governments thus becomes helping workers overcome mobility obstacles and fostering (as smooth as possible) transitions in the labour market, while enabling more efficient allocations of workers and skills across occupations, firms and sectors. Of the many policy tools normally used to address mobility-related issues (e.g. job search assistance through intensive counselling, redeployment benefits or subsidies for geographic relocation), skills policies play an especially important role in the context of digitalisation. Education and training policies can help workers develop the skills needed in the context of ever-changing task contents of occupations and facilitate moving to other jobs, when necessary or desired.

Contributing to this debate, the present study aims to inform governments on the design of well-targeted and cost-effective training policies that can facilitate workers' progressions and transitions in the labour market. Building on the literature on human capital specificity (Neal, 1995; Parent, 2000; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schoenberg, 2010), it analyses the distance between occupations in terms of skill needs and task content of jobs. The study, which covers 31 OECD and non-OECD countries, relies on the Survey of Adult Skills conducted in the context of the OECD Programme for the International Assessment of Adult Competencies (PIAAC)[2] data. This study makes a clear distinction between task-based skills and cognitive skills, thus overcoming the limits of previous studies generally focusing on single countries and mostly using information about job tasks as proxies for workers' skills.[3,4]

Importantly, by means of characterising occupations on the basis of both the tasks performed on the job and the cognitive skills required for the performance of these tasks, this paper further provides a cross-country assessment of distances between occupations in terms of cognitive skill endowment and task-based skill profiles.[5] The Survey of Adult Skills in fact tests key cognitive skills in literacy, numeracy and problem solving in technology-rich environments, and provides information on a variety of tasks performed by individuals at their workplace, information which is used to build indicators of the main skills related to the performance of tasks on the jobs (see Grundke, Jamet, Kalamova, Keslair and Squicciarini, 2017). These so–called 'task-based skills indicators' reflect cognitive skills (ICT and advanced numeracy) as well as skills related to managerial activities, accountancy and selling, self-organisation and readiness to learn. Differences in occupations are characterised in terms of combinations or bundles of skills instead of distances in individually considered skills, in line with previous work on the importance of skills bundles for industrial specialisation and integration in global value chains (Grundke, Jamet, Kalamova and Squicciarini, 2017).

As most governments face budget constraints and changing jobs may require substantive investment in skills, it is important to assess the quantity and type of training needed to facilitate labour market transitions. In a first step, this study estimates the skill distances between occupations using PIAAC information on two cognitive skills, i.e. literacy and numeracy, to proxy workers' general skills and their overall ability to learn. It further provides a first indication of the training needed to transition from one occupation to another. To this end, it follows the approach of Nedelkoska et al. (2015) to proxy the necessary training by the years of education (or parts thereof) corresponding to the differences in cognitive skills between occupations.

In a second step aimed to understand which type of training, in terms of the task content of jobs, could facilitate mobility on the labour market, the analysis focuses on the five task-based skills identified in Grundke et al. (2017).[6] To this end, distances between occupations in terms of task-based skills requirements are estimated using information on: ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills and self-organisation skills.

In the context of the Going Digital horizontal project, this analysis is being complemented by work on the risk of automation by occupation which relies on job-task information, as well as industry and technology-related data. This analysis aims to identify possible labour market trajectories helping workers move away from automatable occupations and minimising education and training costs, as well as human capital losses (e.g. triggered by moves to occupations for which workers are over-skilled). The ultimate goal is to inform policy makers on how to design cost-effective education and training policies and to address the consequences of the digital transformation on labour markets. In addition, analysis will focus on how the retraining costs for affected workers differ according to age, as acquiring the skill mix needed to move to another occupation might be much more costly for elderly workers.

The remainder of the paper first reviews the literature on human capital specificity, the task-content of occupations and the impact of digitalisation on employment and skills. It then briefly presents the methodology developed to measure the distance in terms of skill requirements between occupations. With skill differences between occupations thus identified, it proceeds to give a first indication of the education and training needed to facilitate workers' transition between occupations. Finally, it provides a discussion on the results and possible extensions of the analysis, as well as on the policy implications of this study.

Labour market mobility and skills' needs: what do we know? An overview of existing studies

Labour market mobility may be shaped by a variety of factors. The human capital acquired through work experience which is specific to a (limited) number of jobs or firms, as opposed to general human capital developed thanks to schooling (Becker, 1964), may hinder job change and affect workers' mobility in the labour market (Farber, 1999; Wasmer, 2006). Also, when specific skills are involved, displacement may lead to wage losses, wage inequality, or unemployment (Ljungqvist and Sargent, 1998; Violante, 2002; Poletaev and Robinson, 2008).

Labour market mobility is also influenced by labour market policies, as they shape hiring and separation practices (Ljungqvist, 2002; Pries and Rogerson, 2005; Bassanini and Garnero, 2012) and shape incentives to relocate geographically (Bertola and Ichino, 1995; Hassler et al., 2005). Finally, social protection systems relating entitlements to jobs are currently failing to address many issues related to non-standard forms of work and may contribute to trap individuals in bad jobs or in unemployment (OECD, 2017a).

Task-specific human capital and skills transferability

Existing research on human capital distinguishes between general skills, such as those acquired through education, and job or firm specific skills that are not perfectly mobile across employers. Assessing the extent of human capital "specificity" is thus important, as this form of human capital is likely to be partly lost when job reallocation or displacement occurs.

Following Becker (1964), a first strand of studies focusing on firm-specific human capital provides mixed evidence regarding its effect on individual wage growth (Abraham and Farber, 1987; Topel, 1991; Farber, 1999; Altonji and Williams, 2005; etc.). A second strand of this literature conversely emphasises the role of industry-specific or occupation specific human capital. Using a sample of job displacements due to plant closure, Neal (1995) shows that wages partly reflect compensation for industry-specific skills. Parent (2000) finds that controlling for total experience in the industry substantially reduces the effect of net tenure on wages. In contrast, other studies argue that when occupational tenure is accounted for, industry-specific human capital plays only a minor role. According to Kambourov and Manovskii (2009), industry codes were designed based on the products produced and not on the type of work actually performed by workers. Hence, they argue, human capital specificity should be assessed at the occupation level and Kambourov and Manovskii (2009) show that returns to occupational tenure are sizeable.

More recent empirical studies rely on task-level data to assess the implications of task-specific human capital and skills for workers' labour market transitions and outcomes. Unlike firm, occupation or industry tenure-related variables used in previous studies, task-based data allow examining the degree of task similarity between jobs. This new literature focuses on skills requirements - the so-called "task contents of jobs" (e.g. Autor et al., 2003; Ingram and Neumann, 2006; Yamagushi, 2012[7]) - and argues that, when individuals change occupations, their task-specific human capital is not fully lost if they continue to perform similar tasks in their new occupation. Seeking to identify the costs associated with workers' turnover, several studies build measures of distance between jobs in terms of underlying skills and tasks that these jobs require.

How distant are jobs in terms of skill requirements?

Poletaev and Robinson (2008) use the factor analysis method of Ingram and Neumann (2006) to construct four measures of basic skills based on job task data from the United States' Dictionary of Occupational Title (DOT). These four skill measures are used to characterise the skill portfolio of jobs, construct a measure of skill distances between jobs and assess switching costs. To this end, the authors use a Euclidian distance method and compute skill similarity measures between occupations aimed to identify which workers modify their skill portfolios when changing jobs. They find that switches in skill portfolios are associated with the most substantial wage losses; put differently, workers who avoid large wage losses after displacement are those who find jobs with similar skill requirements to their earlier jobs. Poletaev and Robinson (2008) also investigate the industry-specific human capital issue and find that when task-based skills are taken into account, the role of industry specificity is substantially lower. While the distance measure put forward by Poletaev and Robinson (2008) has the advantage of being computationally simple it does not account for the direction of the required skill change, that is whether individuals need to upskill or down-skill in their occupational moves.

In a similar vein, Gathmann and Schoenberg (2010) examine the transferability of skills across occupations using individual level data from the German Qualification and Career Survey (QCS). The QCS includes information on whether workers perform certain tasks on the job and whether those tasks are the main activity on the job. The skill content of an occupation is characterised based on the shares of workers performing each of the 19 tasks described in the survey. As a measure for similarities between occupations, Gathmann and Schoenberg (2010) use the angular distance of these 19 skill vectors. Such a measure has the drawback of mirroring the relative importance of skills in an occupation. This means that if one occupation requires the same relative ratio of skills as another one, but all skills are needed to a lesser extent, the distance between the two occupations is zero. Similarly to Poletaev and Robinson (2008), Gathmann and Schoenberg's (2010) distance measure is symmetric and does not allow taking into account possible differences between occupations in terms of absolute intensity of skill requirements. For example, while both managers and salespeople may require the same relative intensity in negotiation skills, the absolute intensity of skill requirements is not identical (the managers might e.g. need higher levels in negotiation skills) and this may impact on the possibility of switching between the two occupations.

The present work is more closely related to that by Nedelkoska et al. (2015) who examine whether skill mismatch is responsible for the earnings losses of displaced workers. Using German QCS and longitudinal administrative data, Nedelkoska et al. (2015) propose a measure of skill similarities between occupations that takes into account both the distance and the direction (upward/downward) of occupational switches in terms of human capital. Occupation-level skill profiles are built by calculating the share of workers in an occupation carrying out a particular task and relying on factor analysis to extract five task-based skills. Information on the average number of years of cumulative schooling of workers in a given occupation is then used to assess the number of years of education required to acquire the skills in that occupation's profile. To this end, the variable years of schooling is regressed on the five task-based skills and the regression coefficients are used as weights for the five skills when computing the skill shortage and skill redundancy indicators for each possible switch between occupations.

Nedelkoska et al. (2015) rely on these indicators to examine the effect of job displacement on occupational moves, and their skill measure accounts for possible asymmetries in the transferability of skills between occupations. While this feature of Nedelkoska et al. (2015) represents a clear improvement with respect to existing skill distance measures, their choice of education years to quantify the distance between occupations (and the consequent assumption that task-intensities on the current job are more likely to be influenced by schooling rather than previous work experience) may be subject to scrutiny. This paper therefore relies on a slightly different approach in order to assess the training required to move from an occupation to another, approach which is detailed in the empirical analysis section.

Technological change and skills

A wide array of studies looking at the impact that technological change and computerisation may have on the type of tasks performed on the job shows that not all workers are affected to the same extent and that the ultimate effect depends on workers' skills and on the task-content of jobs. Also, technological progress has been associated with an increasing demand for relatively more skilled workers in comparison to low-skilled ones. This so-called "skill-biased technological change" hypothesis has been put forward to explain the rise in wage inequality between skilled and unskilled workers observed over the past decades.

According to the skill-biased technological change view, technology complements skilled workers, whereas unskilled workers are more prone to be substituted away by technology (Acemoglu and Autor, 2011). When the supply of skilled workers is not sufficient to cover the increased demand triggered by technological change, returns to skills increase, reflecting this skill-biased change. This is in line with what observed, e.g., in the United States, where returns to skills have increased in recent years despite similar increases in the supply of college graduates.[8]

However, the skill-biased technological change hypothesis cannot account for the non-monotone employment growth observed along the skill distribution: the share of jobs featuring intermediate skill levels has grown at a much lower rate than that of high-skilled or low-skilled jobs. This job polarisation phenomenon, as it is often denoted, has been accompanied by a similar movement in the wage distribution (see e.g. Autor and Dorn, 2013, and Cortes, 2016).

More recent studies therefore focus on the task-content of jobs to examine the role of technological change in shaping jobs and skills. This strand of the literature holds that computers and ICT more broadly, tend to substitute workers performing routine tasks while they complement jobs featuring more complex, non-routine tasks related to problem-solving or communication (Autor et al., 2003; Marcolin et al., 2016b). It predicts that workers will continue to perform the tasks for which they have a comparative advantage compared to computers (Autor, 2015).[9]

The data: the OECD Survey of Adult Skills

This work relies on the OECD Survey of Adult Skills, an international survey of individuals that is representative of the population aged 16 to 65. Data were collected in 2011-12 for the first round (22 OECD countries and Russia, OECD, 2013) and in 2014-2015 for the second round (six OECD countries, plus Singapore and Lithuania, OECD, 2016a). The present analysis includes both rounds of PIAAC, to shed light on the skill requirements and task content of occupations for as many countries as possible: overall, the database contains information on 208 620 individuals of which about two thirds (i.e. 138 605 were employed at the time of the interview).

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, thus partially matching the set of cognitive skills assessed through the tests. It also includes information on the frequency of the performance of other types of tasks such as those related to management, communication, organisation and planning, and physical work. Moreover, PIAAC gives information on workers' attitude towards learning, trust, health and other issues, which are gathered through self-reported assessments. Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017) use this additional information on the tasks that workers perform on the job as well as the self-reported information on workers' attitudes and personality traits to conduct an exploratory factor analysis and extract six indicators capturing workers' cognitive, non-cognitive and social skills (see first column of Table 1).

As the present analysis aims to rely on information related to workers' skills and the tasks performed on the job, and to encompass both cognitive and non-cognitive skills, the measures for cognitive skills from PIAAC are combined with the measures for cognitive, non-cognitive and social skills detailed in Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017). These six task-based skill indicators and the items of the PIAAC background questionnaire on which they build are presented in Table 1. The six skill indicators mirror: information and communication technologies (ICT)-related skills; advanced numeracy skills; accountancy and selling skills; non-cognitive skills such as managing and communication and self-organisation; and socio-emotional skills such as readiness to learn (see Table 1).

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

Indicator of job related skill requirements	Items included in the construction of the indicator
ICT Skills	G_Q05e Frequency of excel use G_Q05g Frequency of programming language use
	G_Q05d Frequency of transactions through internet (banking, selling/buying)
	G_Q05a Frequency of email use G_Q05c Frequency of simple internet use
	G_Q05f Frequency of word use
	G_Q05h Frequency of real-time discussions through ICT Computer
	G_Q01b Frequency of Reading letters, emails, memos
	G_Q02a Frequency of Writing letters, emails, memos
	G_Q06 Level of Computer Use required for the job
	F_Q06b Frequency of working physically over long periods
Readiness to learn	I_Q04j I like to get to the bottom of difficult things
	I_Q04m If I don't understand something, I look for additional information to make it clearer
	I_Q04h When I come across something new, I try to relate it to what I already know
	I_Q04b When I hear or read about new ideas, I try to relate them to real life situations to which they might apply
	I_Q04d I like learning new things
	I_Q04l I like to figure out how different ideas fit together
Managing and Communication	F_Q04b Frequency of negotiating with people (outside or inside the firm or organisation)
	F_Q03b Frequency of planning activities of others
	F_Q02b Frequency of instructing and teaching people
	F_Q02e Frequency of advising people
	F_Q04a Frequency of persuading or influencing others
Self-Organisation	D_Q11a extent of own planning of the task sequences
	D_Q11b extent of own planning of style of work
	D_Q11c extent of own planning of speed of work
	D_Q11d extent of own planning of working hours
Accountancy and Selling	G_Q01g Frequency of Reading financial invoices, bills etc.
	G_Q03b Frequency of Calculate prices, costs, budget
	G_Q03d Frequency of using calculator
	F_Q02d Frequency of client interaction selling a product or a service
Advanced Numeracy	G_Q03f Frequency of preparing charts and tablesG_Q03g Frequency of Use simple algebra and formulasG_Q03h Frequency of Use complex algebra and statistics

Source: Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017), based on PIAAC.

Assessing occupational distances: the empirical approach

To shed light on the extent to which occupations differ in terms of their skill requirements and task-content, this study relies on the methodology of Nedelkoska et al. (2015). The latter combines the multidimensional focus on bundles of skills from previous occupation distance measures (Politaev and Robinson 2008, Gathman and Schoenberg 2010) with the notion that occupation distances are not symmetric.

A large literature investigating asymmetries between workers' educational attainment and the educational requirements of their jobs (e.g. Hartog 2000, Leuven and Oosterbeek, 2011) emphasises that, when switching occupations, workers might be in shortage or in excess of certain skills. On the one hand, some may be under-qualified for the job and in need to upgrade their skills; others may have skills in excess to what required or needed, that is workers are overqualified and some of their skills might be redundant. Despite this, existing measures of occupation distances, while focusing on a wide array of skills' needs (or their task-content), have not taken into account the direction of such multidimensional skill (or task) differences between occupations. By combining the multidimensionality of existing occupation distance measures with a metric able to capture asymmetries in needs and endowments, the new method by Nedelkoska et al. (2015) addresses this shortcoming. It allows identifying the set of skills required in higher levels by occupation A as compared to occupation B, as well as the set of skills needed to a lower extent in occupation A as compared to occupation B.

This is important to inform labour market and training policies on how to most efficiently and effectively support the mobility of workers from one occupation to another. This entails identifying the occupational switches requiring (relatively) little additional (re)training (as compared to other possible job changes), which is the case when the occupation of origin and the one of destination feature similar skill requirements i.e. they have a small occupational distance. Also, it helps understanding which types of skills need to be particularly improved in case distances between two occupations are large.

Moreover, the measure of Nedelkoska et al. (2015) allows quantifying the differences in skill requirements between two occupations in terms of the years of education corresponding to the observed cognitive skill difference of the jobs considered. Although adult learning and workers' (re)training might importantly differ from formal learning in a schooling environment, these estimates can nevertheless help provide a first approximation of the training needed for re-training workers for a specific occupational move. Future work will build on these training time figures to provide estimates of the cost entailed by the needed retraining efforts, which will also include the indirect costs of training, as done in Squicciarini et al. (2015) when estimating the cost of training.

To adapt the methodology of Nedelkoska et al. (2015) to the PIAAC data set, several minor changes have been implemented in the analytical procedure. First, PIAAC data allow obtaining six task-based skill indicators at the individual level (Grundke et al. 2017), whereas Nedelkoska et al. (2015) extract task-based skill factors at the occupational level.

Second, the PIAAC data set includes 31 OECD and non-OECD countries, whereas Nedelkoska et al. (2015) conduct their analysis using data for Germany only. Relying on data for 31 countries represents a major advantage in terms of the scope of the analysis, and the implications for policy that it may bring. However, due to the low country-specific size of the samples (around 3500 individuals on average by country), the analysis can only be conducted at a sufficiently disaggregated occupation level (i.e. three digit

ISCO-08), if large groups of countries are combined. Thus, in the baseline of this study occupation distances are analysed at the three digit ISCO-08 level across all 31 countries, implicitly assuming that no major differences in terms of skill requirements and task-content exist across countries within three digit occupation categories.[10] This assumption is later relaxed. The skill distances between occupations are thus computed across four subsets of countries, clustered together on the basis of their similarity in terms of task-based skill requirements' distribution within ISCO-08 one digit occupations.

Third, in addition to the job task information (which is similar to the data used in Nedelkoska et al., 2015) the PIAAC data set also includes three measures of cognitive skills of workers, i.e. literacy, numeracy and problem solving in technology rich environment. Literacy and numeracy are used in the present analysis to investigate the extent to which occupations differ in terms of the cognitive skills that workers are endowed with.[11] Compared to the task-based skills extracted from the job-task information in PIAAC (Grundke et al. 2017), these two cognitive skills are more general and less task-specific and should enable workers to learn and adapt to different work contexts.

Summarising, the occupation distance analysis is conducted here in two complementary steps. The first step investigates occupational distances in terms of cognitive skills and tries to capture individuals' general ability to learn. In a second step, the distances between occupations are analysed in terms of their task content using the five task-based skill indicators from Grundke et al. (2017). This allows looking at the specific type of task-based skills driving the skill difference between two occupations, and identifying key (re)training needs, which would help workers move workers from one occupation to another.

Measuring occupation differences in terms of cognitive skills

In a first step, the average literacy and numeracy skill requirements are calculated for the 127 three digit ISCO-08 occupations in the sample. This is done taking the weighted average of the within occupations' individual scores across all 31 countries and using final sample weights for representativeness purposes (for a detailed discussion of the methodology see the Appendix).

Multidimensional skill distances between any two occupations, e.g. A and B, are further assessed using skill shortage and skill excess measures. Assuming a hypothetical move from occupation A to occupation B, the measure of skill shortage is computed for all skills for which occupation B requires higher levels than occupation A. It therefore informs about the type and amount of skills that workers would need to acquire to be able to move from occupation A to occupation B. The measure is calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the destination occupation B. Weighting skill differences on the basis of the importance of the respective skills in the destination occupation B seems a sensible choice, as workers moving from occupation A to occupation B need to first improve their competencies in the skills that are used most intensively in the new occupation (see the methodological appendix for details).

The measure of skill excess is computed for all skills that occupation B requires in lower levels than occupation A. Thus, the excess measure captures the amount of skills needed for occupation A but that are not needed to the same extent in occupation B. Similar to the shortage measure, the excess measure is calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the origin occupation A. It is important to notice that the shortage and excess measures are symmetric: shortage measures for a move from occupation A to occupation B equal the excess measures for a move from occupation B to occupation A.

Table 2. Occupation distances in terms of cognitive skills (in PIAAC skill scores)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	0.0	0.0	0.0	7.6	0.0
Keyboard operators	20.3	0.0	14.6	12.1	0.6	26.2	14.4
Tellers, money collectors and related clerks	5.8	0.0	0.0	1.2	0.0	11.6	0.0
Client information workers	8.1	0.0	3.6	0.0	0.0	14.0	3.5
Numerical clerks	21.2	1.4	15.4	12.9	0.0	27.0	15.2
Material-recording and transport clerks	1.8	0.0	0.0	0.0	0.0	0.0	0.0
Other clerical support workers	5.9	0.0	0.1	1.2	0.0	11.8	0.00

Note: The Table shows an extract from the occupation distance matrix calculated using the cognitive skills literacy and numeracy, whereby the scale for PIAAC cognitive skill scores ranges from 0-500. The full matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures are calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table 2 shows an extract from the occupation distance matrix calculated using the cognitive skills literacy and numeracy. The full matrix includes 127 three digit ISCO-08 occupations, i.e. it has 127 rows and 127 columns. For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The measures of shortage and excess for the cognitive skills are expressed in PIAAC scores and range from 0-500.

For example, moving from the occupation "Numerical Clerks" to the occupation "Client Information Workers" entails a skill shortage of zero (from column to row), which means that numerical clerks workers have at least the same competencies or higher competencies in all considered cognitive skills than those of client information workers. Hence, a move for workers from the occupation "Numerical Clerks" to the occupation "Client Information Workers" does not require any up-skilling or re-skilling. However, when moving from the occupation "Client Information Workers" to "Numerical Clerks" (from column to row), a skill shortage of 12.9 PIAAC skill scores exists. This means that workers considering moving would need to acquire higher literacy and numeracy skills equivalent to around half of the average difference in literacy scores between adults having completed tertiary education and those having completed upper secondary education in OECD countries (OECD 2016b).

Furthermore, the approach of Nedelkoska et al. (2015) also allows quantifying the differences in skill requirements between two occupations in terms of the years of education corresponding to the cognitive skill difference. Thus, this approach can be used to provide a first indication of the education and training needed to transition from one occupation to another. This is proxied by the years of formal education corresponding to the differences in required cognitive skills between occupations. Although adult learning for the (re)training of workers might be substantially different from formal learning in a schooling environment, these estimates can nevertheless provide a first approximation of the time needed to re-train workers for a specific occupational move.

An extract of the results for this analysis is presented in the Appendix Table A2, and the methodological approach is described in more detail in the methodological appendix. For instance, Table A2 indicates that the upskilling in cognitive skills needed to move from the occupation “Secretaries (General)” to “Numerical Clerks” is equivalent to about 0.8 years of education, whereas moving from the occupation “Numerical Clerks” to any other listed occupation does not require any upskilling in cognitive skills. In future work, this proxy for the time needed to retrain workers for an occupational move will be combined with external data on training costs to give an indication of the required training investment needed.

Measuring occupation differences in terms of task-based skills

To evaluate the distance between occupations in terms of their requirements in task-based skills, this study relies on the five task-based skill indicators proposed in Grundke et al. (2017) and presented in Table 1, namely: ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills as well as self-organisation skills. For the presented analysis, the task-based skill scores have been standardised across countries.[12]

As for the cognitive skills, in a first step, the average skill requirements in terms of task-based skills are calculated for the 127 three digit ISCO-08 occupations in the sample by taking the weighted average of the individual scores within occupations across all 31 countries, using final sample weights (for a detailed discussion of the methodology see the Appendix). Skill shortage and skill excess measures are then computed between any two occupations A and B, to assess the direction of the differences in skill levels between the two occupations.

Assuming a hypothetical move from occupation A to occupation B, the measure of skill shortage is computed for all task-based skills for which occupation B requires higher levels than occupation A. It therefore informs about the type and the amount of task-based skills that workers would need to acquire to be able to move from occupation A to occupation B. The measure is calculated as the weighted sum of the skill differences, with weights based on the relative importance of the task-based skills in the destination occupation B (for details see the methodological appendix).

The skill excess measure is computed for all skills that occupation B requires in lower levels than occupation A and captures the amount of task-based skills needed for occupation A but that are not needed to the same extent in occupation B. Similar to the shortage measure, the excess measure is calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the origin occupation A. Again, the matrix is symmetric: the shortage measure for a move from occupation A to occupation B equals the excess measure for a move from occupation B to occupation A.

Table 3. Occupation distances in terms of five task-based skills

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	2.0	0.9	0.9	0.1	0.9	1.0
Keyboard operators	0.0	0.0	0.2	0.0	0.0	0.3	0.2
Tellers, money collectors and related clerks	1.0	2.5	0.0	0.9	0.6	1.3	1.3
Client information workers	0.3	1.5	0.2	0.0	0.4	0.5	0.5
Numerical clerks	0.9	2.9	1.3	1.8	0.0	1.8	1.9
Material-recording and transport clerks	0.2	1.8	0.5	0.5	0.3	0.0	0.3
Other clerical support workers	0.1	1.4	0.3	0.3	0.2	0.1	0.0

Note: The table presents an extract of the occupation distance matrix calculated using the five task-based skills. Task-based skills measures are standardised across countries so that the standardised skill scores have mean zero and standard deviation equal to 1. The full matrix includes 127 three digit ISCO-08 occupations, i.e. 127 rows and 127 columns. For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is relates to a move from the column occupation to the row occupation, whereas the excess measure refers to a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the shortage and excess measures reflect the relative importance of task-based skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table 3 presents an extract of the occupation distance matrix calculated using the five task-based skills, with the task-based skill indicators standardised across countries, so that they have mean zero and standard deviation one. The original matrix includes 127 three digit ISCO-08 occupations, i.e. 127 rows and 127 columns. For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation; the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column).

Taking the same example made in the case of cognitive skill distances, Table 3 shows that moving from the occupation "Numerical Clerks" to the occupation "Client Information Workers" entails a skill shortage of 0.4 points (from column to row). This means that for some task-based skills the numerical clerk workers have lower competencies than workers in the occupation "Client Information Workers" (although their cognitive skills are on average higher, as mentioned before). A move would hence require some up-skilling in certain task-based skills. Conversely, when moving from the occupation "Client Information Workers" to the occupation "Numerical Clerks (column to row), a skill shortage of 1.8 points exists, which means that in some other task-based skills the workers in client information have lower competencies than numerical clerks.

In the case of the task-based skills, no equivalence of the skill distance in terms of formal education years necessary to acquire these skills is computed. The reason is that the schooling requirements equation would not be correctly specified: primary, secondary and tertiary education are reasonably related to cognitive skills but only to a lesser extent to task-specific skills, which are likely to be mainly formed and transmitted through e.g. learning-on-the-job.[13]

Robustness checks: testing the sensitivity of estimates to different specifications

Conducting the analysis for subsets of countries

As mentioned, the baseline specification followed in this study analyses occupation distances using measures of average skill requirements within 3 digit ISCO-08 occupation categories across all the 31 countries considered. Doing so implicitly entails assuming that no major differences exist across countries within three digit occupation categories, in terms of skill requirements and task-content. This assumption is relaxed to try and see whether and to what extent countries differ in their occupational skill requirements.

To this end, the analysis is conducted on four subsets of countries which are similar with respect to their occupational skill requirements. Countries are grouped on the basis of cluster analysis assessing similarities in terms of the distribution of the task-based skill requirements within one digit ISCO-08 occupations. For the cluster analyses, the Euclidean distances between countries have been computed using to the following variables: the 25th, 50th and 75th percentile of each of the distributions of all five task-based skills within each of the nine ISCO-08 one digit occupations - in sum 135 variables. Regardless of the specific type of cluster analysis tried, the four country clusters shown in Table A3 are found to be robust sets of countries and display similar occupational skill requirements (for further details see the methodological appendix).

The matrices for the occupation distances in terms of cognitive skills and in terms of task-based skills are computed for each of the clusters. The tables A4-A7 show extracts from the matrix of cognitive skill distances between occupations based on the cluster analysis. From the sub-sample of occupations shown here, differences between country clusters exist in terms of the average multidimensional skill requirements of the occupations. These lead to different skill distances between occupations, depending on the cluster considered. Occupation distances nevertheless appear quite similar for the clusters 2-4 as well as the full group of countries, fact which indicates that for the set of countries in clusters 2-4 the analysis based on the full sample might represent a reasonable approximation. This suggests that, in case a sufficient sample size would be available, an analysis of occupation distances conducted on country-specific data would be preferable to conducting the analysis based on cross-country averages.

Including the readiness to learn of workers in the analysis

Because the ability of workers to move between occupations might also depend on workers' readiness to learn, in robustness checks the analysis includes a measure of the readiness to learn and creative thinking of workers to compute skill distances between occupations (described in Table 1). The measure is based on individuals' self-assessment, as explained in Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017). As being ready to learn and to think creatively is arguably important for upgrading all types of skills, i.e. cognitive as well as task-based skills, readiness to learn is included in the computation of occupational distances in terms of cognitive skills and task-based skills (for further details see the methodological appendix).

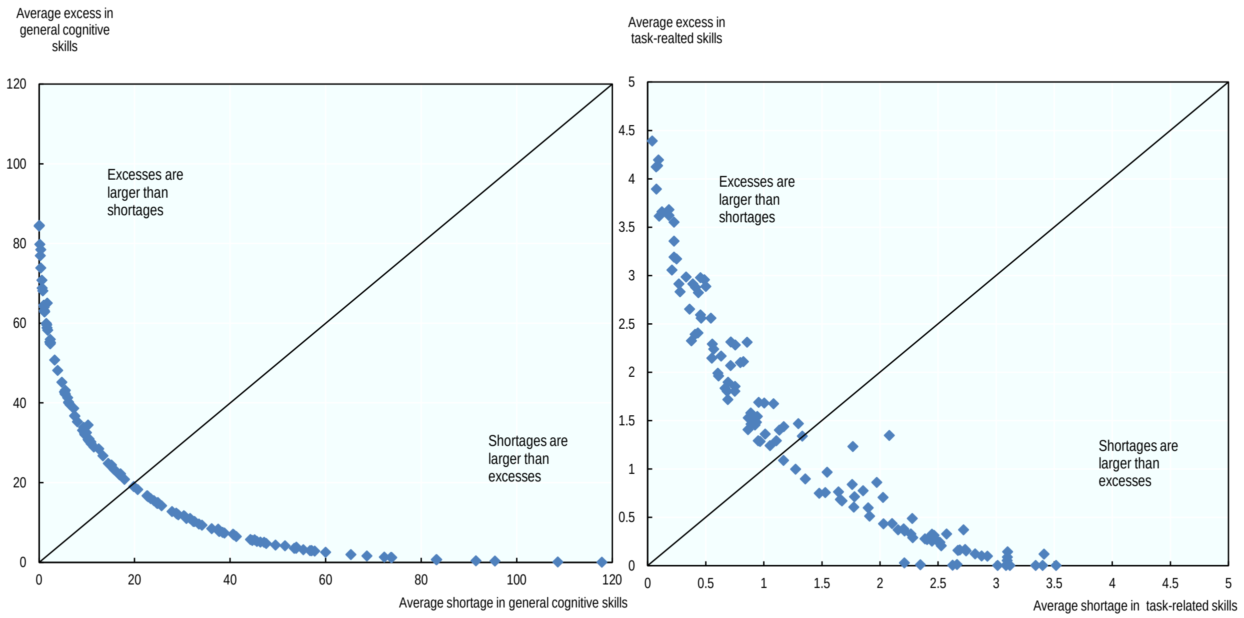
Compared to the baseline results in Table 2 and 3, the results in Table A8 and A9 show that occupation distances differ slightly when readiness to learn is taken into account. While this sheds new light on the role of readiness to learn in shaping skills, both cognitive and non-cognitive, the interpretation of distances based on both elements is non-trivial, as the measure and scale for readiness to learn differs substantially compared to the other measures. It further prevents the benchmarking of the results for the occupation distances in cognitive skills to other studies having used PIAAC cognitive skills.

Results and policy implications

As mentioned, transitions between 3-digit level occupations[14] involve both skills shortages and excesses, and this is true for general cognitive skills (i.e. literacy and numeracy) and task-related skills (i.e. ICT, self-organisation, advanced numeracy, accounting and selling, and managing and communicating) (Figure 1). Moves from high-skilled occupations to other occupations (i.e. those occupations close to the vertical axis in the Figure 1) lead to high skills excesses and little skills shortages. Conversely, switches from low-skilled occupations to other occupations (i.e. occupations close to the horizontal axis in Figure 1) lead to high skills shortages and little skills excesses. Mobility for middle-skilled occupations to other occupations generally involves both substantial skills shortages and excesses. Workers in these occupations would face smaller difficulties to move occupation on average than workers on low-skilled occupations but may also be less motivated to do so, as changing job may mean that they would lose the rewards that some of their skills command, given that some of their skills will be less needed in the new occupation.

Figure 1. Shortages and excesses in general cognitive skills and task-related skills to move between occupations

Average skills distances (expressed in skills excesses and skills shortages) to move from one occupation to any other occupation

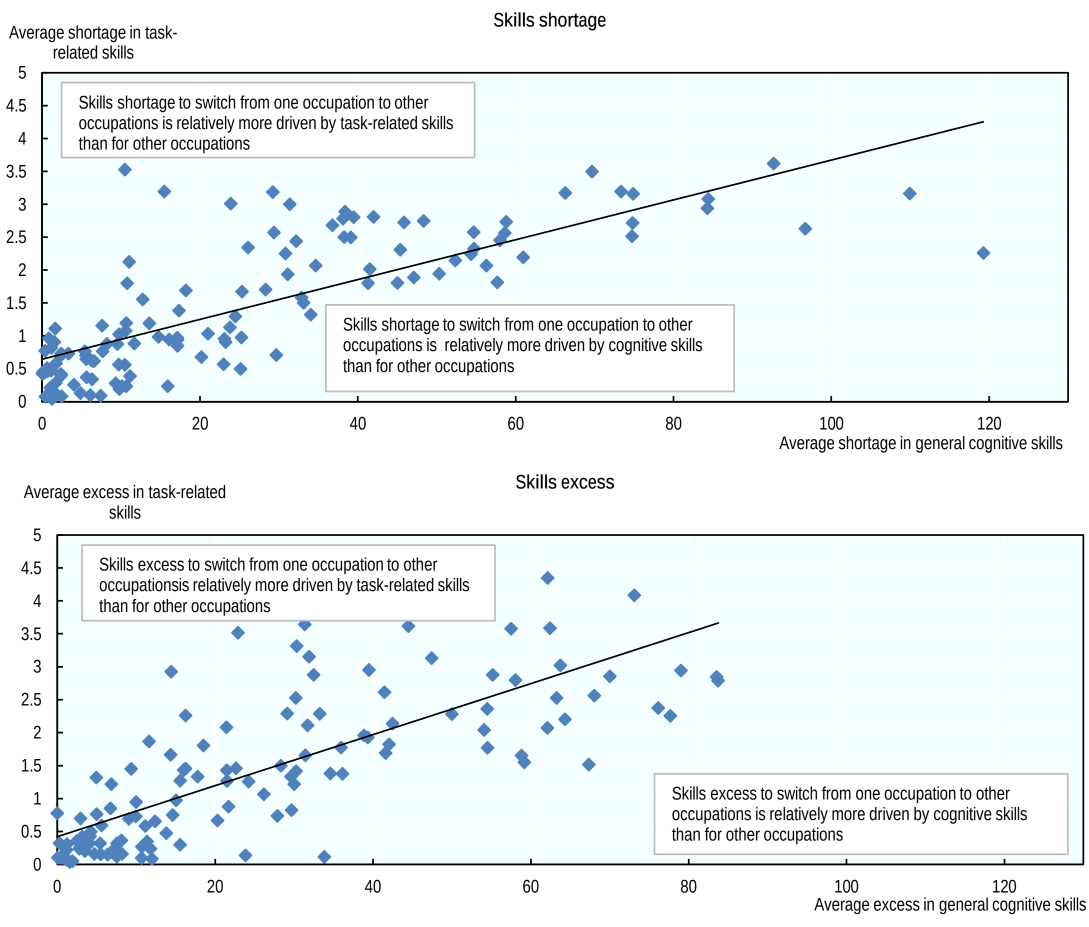


Note: Occupations are analysed at the 3-digit codes of 2008 International Standard Classification of Occupations (ISCO-08). For each occupation, the average shortage (excess) in general cognitive and task-related skills corresponds to the average of the general cognitive and task-related skills shortages (excesses) to any other occupation. Occupations above the line are relatively high-skilled occupations for which transitions involve more skills excesses than shortages, on average. Occupations below the line are relatively low-skilled occupations for which transitions involve more skills shortages than skills excesses, on average.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

The average distance to move from one occupation to any other occupation is associated with shortages in both cognitive skills and task-specific skills, with the shortages in the two skills being roughly in the same proportion for many occupations, though for a group of occupations (above the line) shortages are driven relatively more by task-related skills (Figure 2). This feature is more marked for skills excesses: although for many occupations, switches to other occupations would entail skills excesses in both cognitive skills and task-related skills to the same extent, for a large group of occupations skills excesses are driven relatively more by task-related skills.

Figure 2. Occupation distances in terms of general cognitive skills and task-related skills

Average distance to move from one occupation to any other occupation

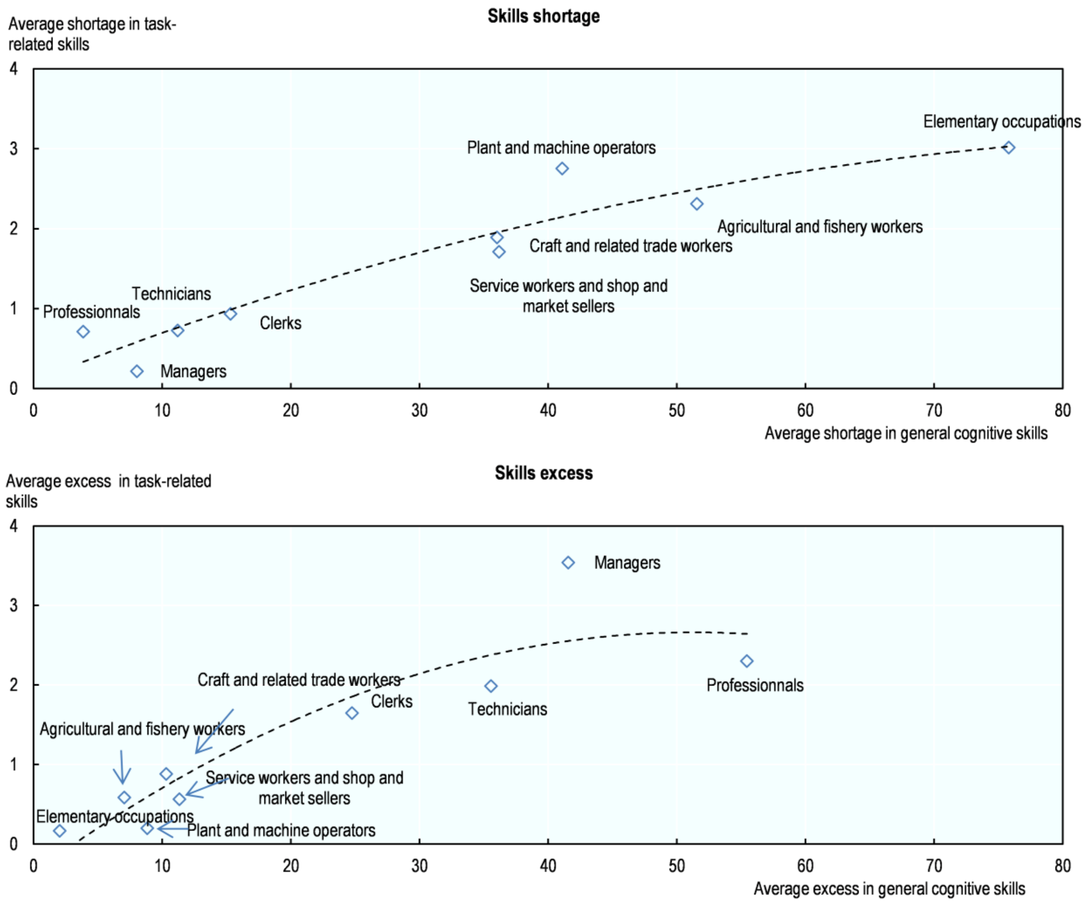


Note: Occupations are analysed at the 3-digit codes of 2008 International Standard Classification of Occupations (ISCO-08). For each occupation, the average shortage (excess) in general cognitive (task-related) skills corresponds to the average of the general cognitive (task-related) skills shortages (excesses) to any other occupation. Occupations above the trend line are those for which the average distance to switch to other occupations is relatively more driven by task-related skills. Occupations below the trend line are those for which the average distance to switch to other occupations is relatively more driven by general cognitive skills.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Occupations for which transitions to any other occupation involve the smallest average skills shortages and the largest average skills excesses are unsurprisingly those belonging to more skilled 1-digit occupations groups[15]: managers, professionals, and technicians (Figure 3). Transitions for occupations belonging in the plants and machine operators group or in the elementary occupations group would involve large upskilling needs with little skills excesses.

Figure 3. Occupation distances in terms of general cognitive skills and task-related skills, occupations group level

Average distance to move from an occupations group (1-digit level) to any other occupation (3-digit level)



Note: Occupations groups are analysed at the 1-digit codes of 2008 International Standard Classification of Occupations (ISCO-08). For each occupations groups, skills shortages and excesses are calculated as the average of the average skills shortages and excesses of all the 3-digit occupations belonging to the considered occupations' group (i.e. as the average of the 3-digit occupations' skills shortages and excesses presented in Figure 2 for that occupations group).
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Statistics on transitions from one occupation to any other occupation help shed light on the effort that may be needed to move on the labour market. If we suppose that workers are more likely to switch to occupations that are relatively closer to their occupation of origin in terms of skills requirements, transitions within the same (1-digit ISCO-08) occupations' group can be considered as relatively "close" transitions, or transitions to similar occupations.

Looking at such close transitions, a generally positive relationship between the average distance for transitions to all other occupations and the average distance for transitions within the 1 digit ISCO-08 group of occupations emerges in terms of cognitive skills (top panel of Figure 4). Such close transitions entail significantly greater shortages in cognitive skills for elementary occupations, but appear relatively small for other low-skilled occupational groups such as plant and machine operators. High-skilled occupation groups such as managers and professionals exhibit about average cognitive skill distances for transitions to close occupations. No clear patterns conversely emerge with respect to a move to similar occupations in the case of medium-skilled occupation groups, as e.g. clerks are far apart from the others and feature the smallest average distance whereas craft and related trade workers display the greatest distance in terms of general cognitive skills.

To put these results in perspective, distances in terms of cognitive skills can be expressed in terms of years of education (see Table A2). Estimates suggest that moves within the group of managers would require on average half a year of education while transitions within the group of elementary occupations would require almost a year of education, on average.

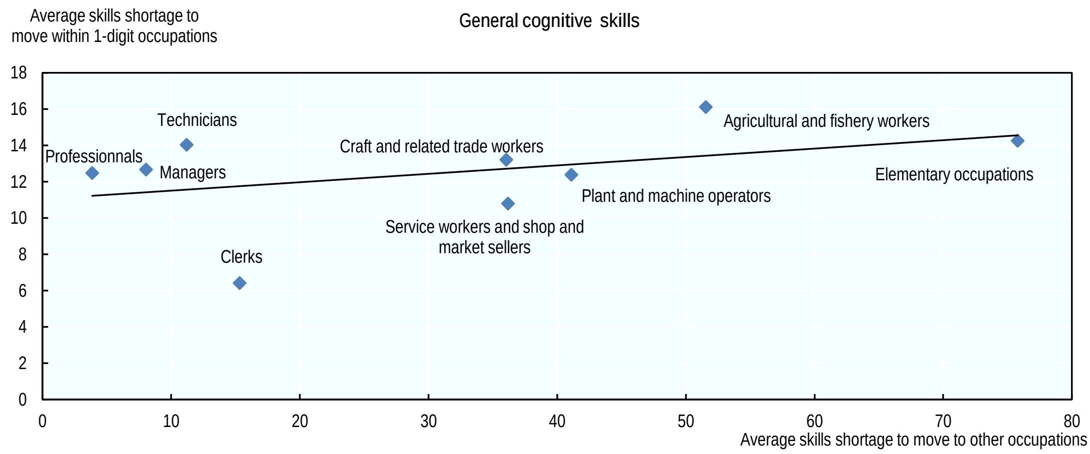
In contrast, distances in terms of task-related skills to move to occupations in the same ISCO-08 1 group are larger for high-skilled occupations groups such technicians, and professionals than for low skilled ones such as plant and machine operators, and for elementary occupations. Managers seem to stand out a bit with an average skills distance for transitions to other occupations within the same one digit ISCO-08 occupation category which is similar to the one of medium-skilled occupations groups such as clerks, and services workers and shop and market sellers.

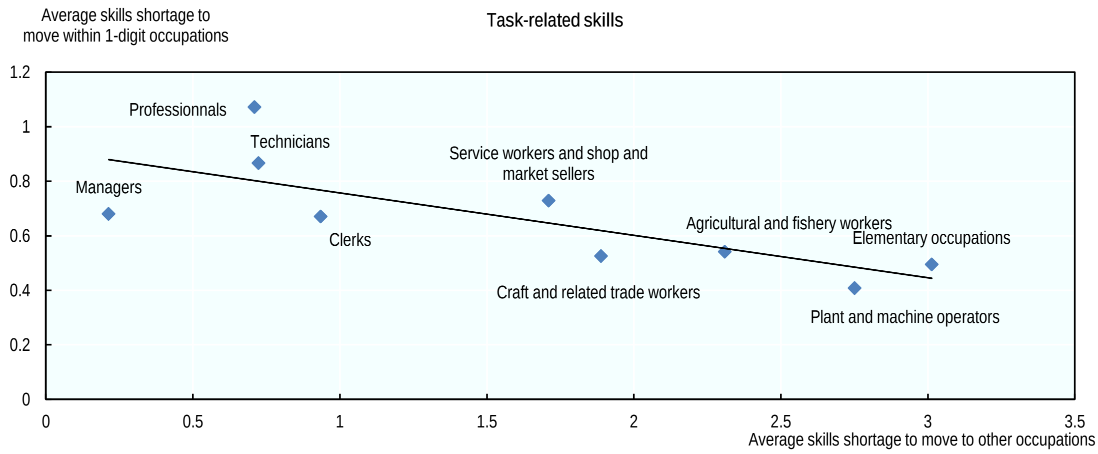
As a caveat to the evidence proposed above it must be noted that the analysis relies only on the skills-related information captured in the Survey of Adult Skills. This represents a subset of all skills and knowledge areas that characterise specific occupations. Despite this, results suggest that the distance measure calculated in terms of task-related skills is able to capture additional information compared to the distance emerging between occupations in terms of general cognitive skills. The relatively large task-based distances characterising the moves of e.g. technicians and professionals within their own occupational groups to some extent reflect the large differences in the type of concrete work done by different types of technicians or professionals. For instance the work of computer technicians differs in comparison to what car or electric appliances technicians may do. Conversely, different types of managers seem to do relatively similar tasks and to use similar levels of cognitive skills independently of their area of expertise, as suggested by the relatively smaller distances characterising moves within this category compared to other high-skilled occupations groups.

Overall, transitions within relatively low-skilled occupations groups may involve greater distances in general cognitive skills but narrower ones in terms of task-related skills. On the one hand, these results suggest that policies helping low-skilled workers to develop skills related to tasks performed on the job could facilitate job mobility. On the other hand, low-skilled workers may face barriers linked to their low basic cognitive skills, which are much more difficult to upgrade at a later age, for a number of reasons (Windisch, 2015). Devising policies which may succeed in bringing these people back to education and/or training at later stages of their life may not be trivial. Also, as knowledge is cumulative and low-skilled people display relatively lower readiness to learn, it may prove challenging for training and education to be successful, beyond simple participation in (re)training programmes. Transitions within relatively high-skilled groups of occupations may involve bigger upskilling needs in terms of skills related to tasks performed on the job but lower ones in terms of general cognitive skills. As workers in these occupation groups are more likely to learn on the job, they are likely to face lower difficulties in managing these transitions.

Figure 4 Skills distance to move within the same ISCO-08 one digit occupation category

Relationship between the average distance for transitions in the same ISCO-08 one digit occupations category and the average distance for transitions to all other occupations



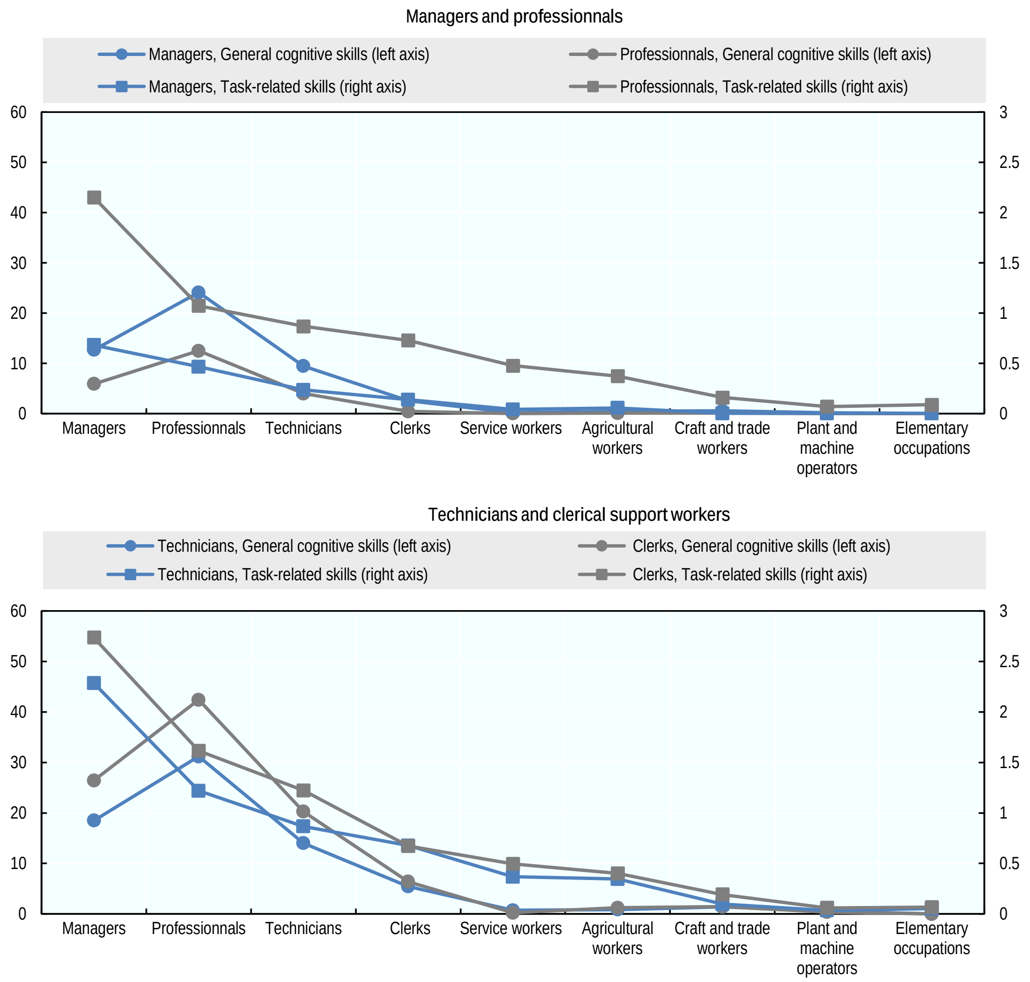


Note: Occupations refer to the 3-digit codes of 2008 International Standard Classification of Occupations (ISCO-08), while occupations group refers to the 1-digit ISCO-08 codes. The average distance (shortage) to all other occupations is calculated as the average of the average shortages of each occupation belonging to that occupations group to all other occupations outside this group. The average distance to move within 1-digit occupations (occupations group) is calculated as the average of average shortage for each occupation to the other occupations belonging to that occupations group.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

The analysis can be extended by looking at average distances between occupation groups. Skills shortages and excesses involved in these transitions are presented in Figure 5 for some middle-skilled and high-skilled occupations groups and in Figure 6 for low-skilled and other middle-skilled occupations groups. Though the figures below display all occupations' group-to-group distances, only transitions to "nearby" occupations groups (in this case 1 to 2 occupations groups to the left) are generally plausible: an elementary occupations worker is unlikely to become a manager but may transition to a plant and machine operator job or perhaps retrain to become a craft and trade worker. Switching from technicians to professionals, from clerks to technicians, from service workers to clerks or from elementary occupations to plant and machine operators would require upskilling in both general cognitive and task-related skills. Technicians willing to move to managerial positions would require mainly developing task-related skills but no significant upskilling in terms of general cognitive skills.

Figure 5. Skills shortages to move to other groups of occupations, high-skilled and middle-skilled occupations groups

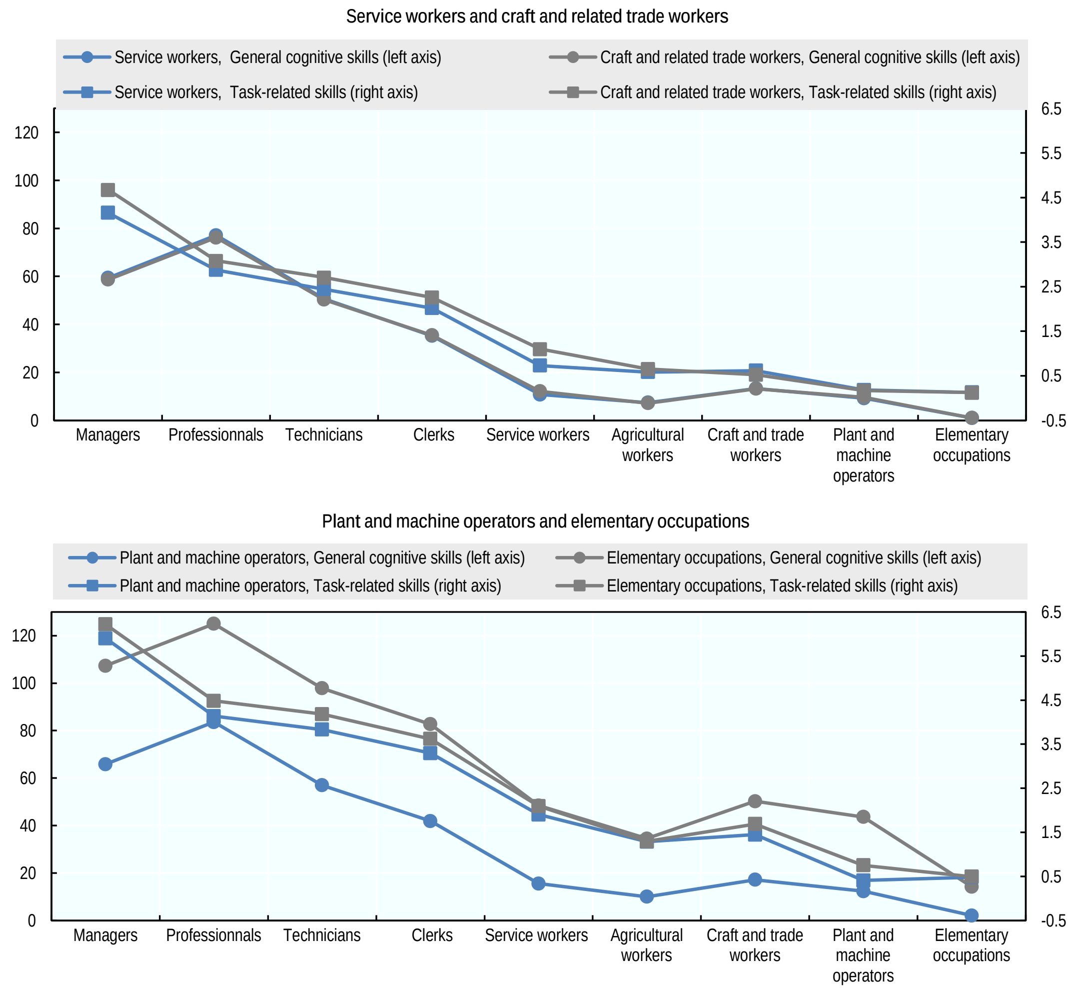
Average shortage to move from a group of occupations to another group of occupation



Note: Each line shows the skills shortage entailed by a move from a given group of occupations (for instance technicians in blue in the top panel) to other groups of occupations, either in terms of general cognitive skills (circles) or task-related skills (squares). The skills shortage related to moves occurring within the occupational group considered relate to moves across occupations belonging to the same ISCO-08 1 digit group.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Figure 6. Skills shortages to move to other groups of occupations, low-skilled and middle-skilled occupations groups

Average skills shortage to move from a group of occupations to another group of occupation



Note: Each line shows the skills shortage entailed by moves from a given group of occupations (for instance service workers in blue in the top panel) to other groups of occupations, either in terms of general cognitive skills (circles) or task-related skills (squares). The skills shortage related to moves occurring within the occupational group considered relate to moves across occupations belonging to the same ISCO-08 1 digit group.

Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

These results help explain the polarisation of employment observed in some countries over the last decades whereby the share of employment in high-skilled (and to some extent in low-skilled) jobs has increased, while the share of employment in middle-skilled jobs has decreased (OECD, 2017a). As transitions from middle-skilled occupations groups such as clerks and service workers to more skilled occupations groups require upskilling in terms of both cognitive and task-based skills, these workers may have instead moved to less-skilled occupations as a result of lower demand for their type of work (and in the absence of adequate training opportunities or the impossibility to train). Policies facilitating transitions from middle-skilled occupations to higher-skilled occupations would require developing both cognitive and task-specific skills, suggesting that on-the-job training might be insufficient.

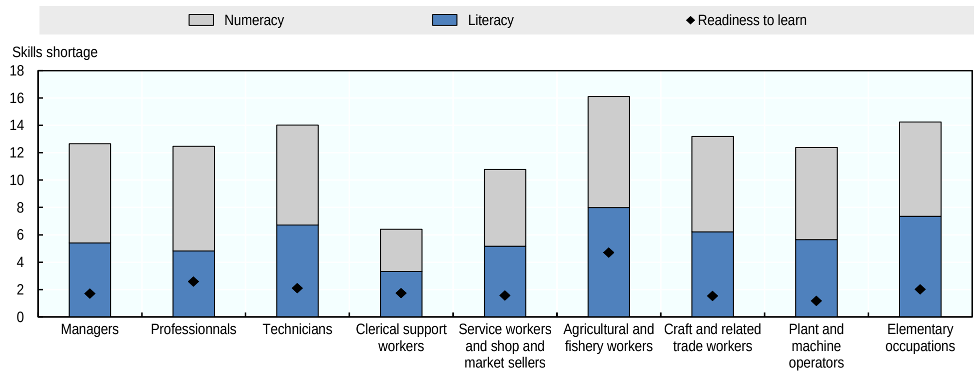
Overall these results show that a comprehensive approach to skills development is needed to facilitate job mobility. Policies to develop task-related skills through learning or training on the job are not enough to facilitate job mobility in a number of cases, for instance within relatively low-skilled occupations and from middle-skilled to high-skilled occupations. Such policies need to be complemented by policies aimed to develop general cognitive skills, through e.g. specific programmes or by enabling workers to go back to formal education. For initial education systems, these results confirm the need to limit the share of young people leaving education with low basic skills, for instance by ensuring that vocational education and training programmes include a strong component on cognitive skills in addition to job-specific skills.

The role of readiness to learn in complementing cognitive and task-based skills

As the ability of workers to move between occupations might also depend on workers' readiness to learn, and the latter may shape both general cognitive and task-related skills, in what follows the analysis decomposes skills distances into cognitive and task-based skills as well as readiness to learn (see Appendix for more details). Transitions to occupations in the same 1-digit ISCO-08 group lead to skills excesses or shortages in both literacy and numeracy skills which are similarly distributed between literacy and numeracy for all groups of occupations (Figure 7). For example, moving within the occupational group of managers would entail average shortages in literacy and numeracy of about 6 and 7 PIAAC skill scores, respectively. For literacy, this is equivalent to about a quarter of the average difference in literacy scores between adults having completed tertiary education and those having completed upper secondary education in OECD countries (OECD 2016b).

Figure 7. Skills distance characterising moves within the same occupation group, by type of general cognitive skills and readiness to learn

Average distance from an occupation to other occupations within the same occupational group

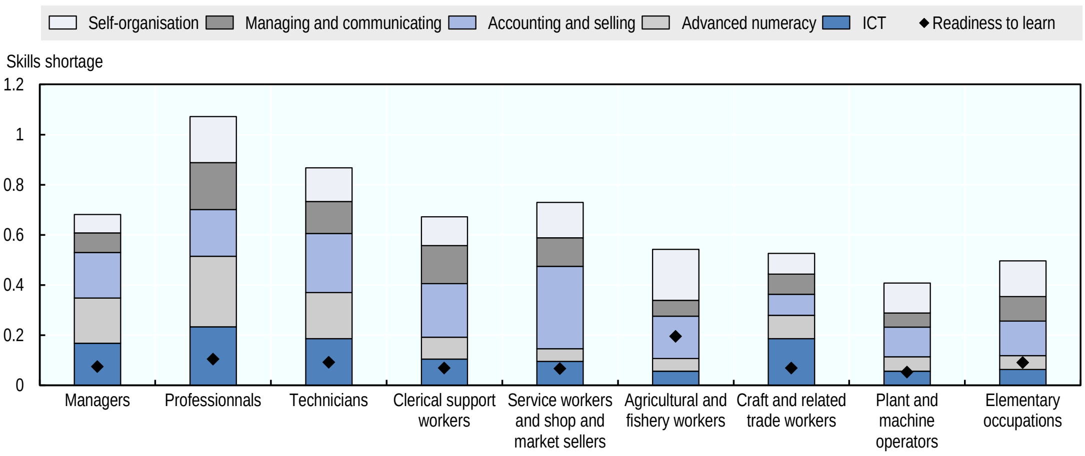


Note: The average distance to move within 1-digit occupations (occupations group) is calculated as the average of average shortage for each occupation to the other occupations belonging to that occupations group. The cognitive skills are measured in PIAAC scores ranging from 0-500. The indicator readiness to learn is based on individuals' self-assessment, as explained in Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017). For the inclusion in the distance measure (in terms of cognitive skills) the indicator is rescaled to the interval 0-500.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Likewise, the transitions to occupations in the same 1-digit ISCO-08 group would also involve skills excess or shortages in all task-related skills generally to same extent for all groups of occupations (Figure 8). One exception is advanced numeracy skills which appear to be needed to a lesser extent when moving within low-skilled occupations.

Figure 8. Skills distance characterising moves within the same occupation group, by type of task-related skills and readiness to learn

Average distance from an occupation to other occupations within the same occupational group



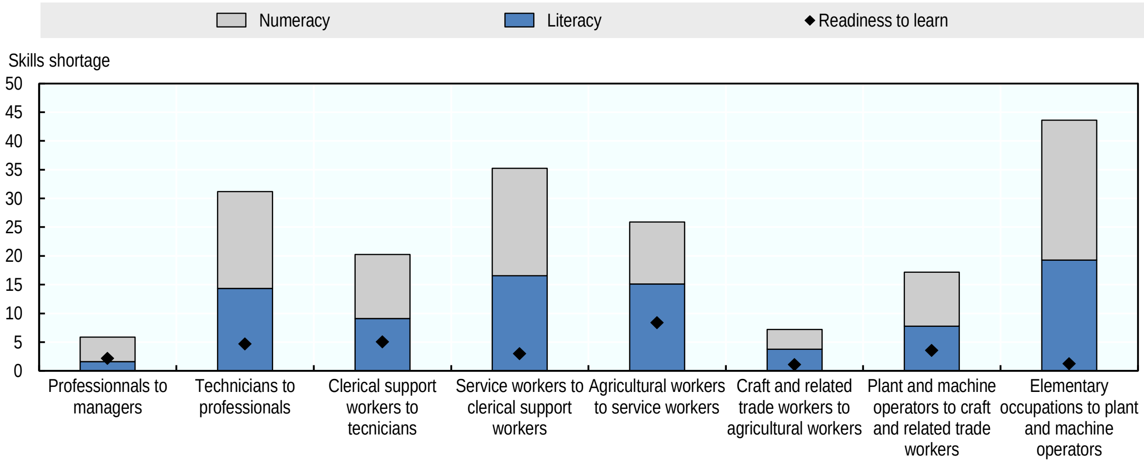
Note: The average distance to move within 1-digit occupations (occupations group) is calculated as the average of average shortage for each occupation to the other occupations belonging to that occupations group. All task-based skills as well as the indicator for readiness to learn have been standardised across countries.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

In the case of transitions to the upper group of occupations, results are similar for the two general cognitive skills considered: both higher literacy and numeracy skills are needed (Figure 9). Differences emerge for task-related skills. Each group of occupations involves a specific mix of skills to be developed for workers to move to the upper group of occupations (Figure 10). For instance, professionals would need to acquire higher accounting and selling and communicating and managing skills to reach managerial positions. Conversely service workers would mainly need to increase their ICT skills to move to clerical support occupations. Being ready to learn seems important for some of these transitions.

These findings suggest that training policies aiming to foster job mobility may need to consider how to develop a range of skills, especially when the aim is to facilitate transitions to occupations that are relatively closer to the occupation of origin. Policies aiming at facilitating transitions to more skilled occupations conversely need to be designed as to target the specific needs of the occupational group considered.

Figure 9. Skills distance to move to the upper group of occupations, by type of general cognitive skills

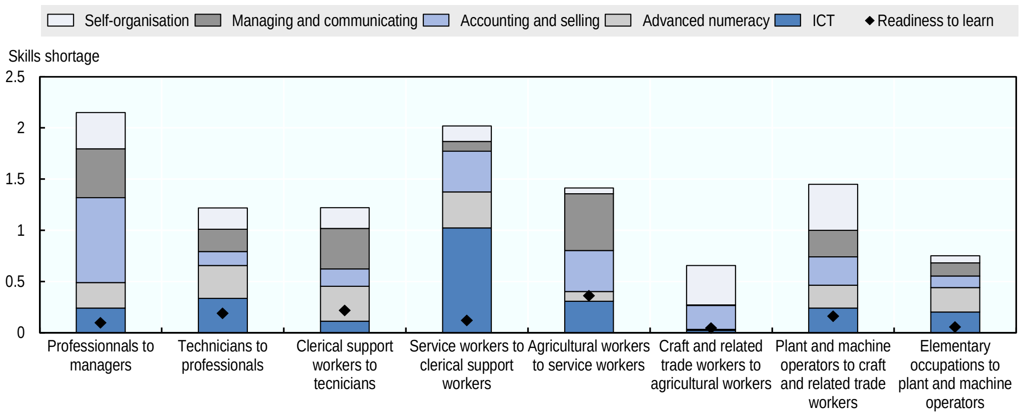
Average distance to move from a group of occupations to the upper group of occupations



Note: The average distance to move from an occupation group (1-digit occupations) to the upper occupation group is calculated as the average of average shortage for each occupation belonging to one occupation group to the other occupations belonging to the upper occupations group. The cognitive skills are measured in PIAAC scores ranging from 0-500. The indicator readiness to learn is based on individuals' self-assessment, as explained in Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017). For the inclusion in the distance measure (in terms of cognitive skills) the indicator is rescaled to the interval 0-500.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Figure 10. Skills distance to move to the upper group of occupations, by type of task-related skills

Average distance to move from a group of occupations to the upper group of occupations



Note: The average distance to move from an occupation group (1-digit occupations) to the upper occupation group is calculated as the average of average shortage for each occupation belonging to one occupation group to the other occupations belonging to the upper occupations group. All task-based skills as well as the indicator for readiness to learn have been standardised across countries.
Source: OECD calculations based on the Survey of Adult Skills (PIAAC) (2012, 2015).

Conclusions and next steps

This work aims to inform governments about the size and content of the training needed to facilitate adaptation to a changing world of work. By analysing the distance between occupations in terms of skills' mix, this paper provides an approach that may help policy-makers identify occupations that are relatively close (in terms of skill requirements) to the ones being changed or made redundant by digitalisation or by any other contingent or structural shock. Identifying those job-to-job transitions entailing the lowest possible effort and cost may further help workers identify which skills to develop or improve to be able to move to such "close" occupations. Education and training policies have an important role to play in this respect but policy makers can also facilitate the adoption of a working environment which is conducive to learning on the job. Since the analysis is carried at a disaggregated level of occupations (ISCO-08 3 digit code), changes between occupations may also be seen as simple progressions in individuals' careers rather than radical switches. Hence, the policies implications of the distance measure developed in this paper are not restricted to the case of displaced workers and concern any type of workers who (are led to) change jobs.

As digitalisation increases uncertainty regarding the future demand for skills, governments might need to take strategic decisions about the type of skill bundles that education and training policies should aim to develop. Skills policies might thus need to be rethought, to find the right balance between endowing individuals with general skills versus providing them with more task-related skills, so as to develop skill sets that make countries fit for the future global market.

One thing that already emerges with clarity from the analysis is that digitalisation increases the need for enhanced synergies between initial education and adult learning, as most occupational moves require upskilling in both, cognitive as well as task-related skills. In this context, this paper informs the debate on the type of skills that training policies may help develop (general vs task-related), thanks to the analysis on the distance between occupations in terms of cognitive skills as well as on in terms of task-content (as a proxy for task-related skills).

Appendix

Methodological Appendix

In the baseline analysis, this study focuses on literacy and numeracy to evaluate the distance between occupations in terms of their cognitive skills' requirements. "Problem solving in technology rich environments" is excluded from the baseline analysis, because this measure is not available for three major European countries (France, Spain and Italy have not participated in the respective assessment tests) and suffers from selection biases in the other participating countries due to individuals refusing or not being able to take the assessment test, especially low-skilled individuals (OECD 2016).[16] Robustness checks including this third cognitive skill into the analysis show that occupation distances do not significantly change compared to the baseline analysis.[17]

In a first step, the average skill requirements in terms of literacy and numeracy are calculated for the 127 three digit ISCO-08 occupations in the sample[18] by taking the weighted average of the individual scores within occupations across all 31 countries, using final sample weights.[19] Using final sample weights entails that larger countries receive a larger weight in the calculation of the averages by occupation.[20] To calculate the multidimensional skill distances between two occupations A and B and to assess the direction of the differences in skill levels between the two occupations (assuming a hypothetical move from A to B), the following two formulas are used:

$$Shortage_{AB} = \sum_{s=1}^{2} w_s(score_B^s - score_A^s)I(score_B^s > score_A^s) \qquad (1)$$

$$Excess_{AB} = \sum_{s=1}^{2} w_s(score_A^s - score_B^s)I(score_B^s < score_A^s) \qquad (2)$$

Whereby $s \in$ (literacy, numeracy) and score is the average score of the skill s (PIAAC scale between 0 and 500) for the occupation *A* or *B* (across 31 countries).

The measure of skill shortage is computed for all skills for which occupation B requires higher levels than occupation A, as captured by the indicator function *I()*. The measure is calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the destination occupation B. The skill with the highest average score in occupation B receives a weight equal to 1. The weight for the other skill is then computed by dividing the average score for the respective skill in occupation B by the average score of the skill with the highest average score. This weighting method is an ad hoc choice and other alternative weighting methods might be used. However, weighting skill differences on the basis of the importance of the respective skills in the destination occupation B is sensible, as for workers moving from occupation A to occupation B it is most important to improve their competencies in the skills that are used most intensively in the new occupation.

Similar to the shortage measure, the measure of skill excess is computed for all skills that occupation B requires in lower levels than occupation A.[21] Thus, for any hypothetical move from occupation A to occupation B two measures exist. The shortage measure reflects the additional amount of skills needed in the new occupation B. The excess measure captures the amount of skills needed for occupation A but that are not needed when moving from occupation A to occupation B. It is important to notice that matrices are symmetric: the shortage measure for a move from occupation A to occupation B equals the excess measure for a move from occupation B to occupation A.

To provide a first indication of the training needed to transition from one occupation to another, the approach of Nedelkoska et al. (2015) is applied, whereby training needs are proxied by the years of education corresponding to the differences in required cognitive skills observed for the two occupations considered. To calculate skill distances in terms of education years, the following OLS regression is estimated for all 127 occupations in our sample, with within occupation averages of individual scores calculated across all 31 countries using final sample weights:

$$education_{occ} = \beta_0 + \beta_1 literacy_{occ} + \beta_2 numeracy_{occ} + u_{occ} \qquad (3)$$

The dependent variable, $education_{occ}$ is the average years of formal schooling during lifetime (across workers within the occupation), which includes primary, secondary and tertiary education as well as formal schooling during the working life of the individual.[22] The independent variables considered correspond to the average cognitive skills literacy ($literacy_{occ}$)and numeracy ($numeracy_{occ}$) . Equation (3) assumes that the cognitive skills literacy and numeracy are formed and transmitted by primary, secondary and tertiary education as well as other formal schooling of workers. It also assumes that the schooling requirements for different skills are additive. Robust standard errors are used.

The coefficients $\beta 1$ and $\beta 2$ can be interpreted as the number of years of additional education it takes to acquire an increase in the corresponding skill by one point (in the scale of 0-500; ceteris paribus). Results in Table A1 (col. 1) show that literacy has the strongest association with years of education, whereby an increase of literacy by twenty additional points requires 1.12 additional education years. Although numeracy is less strongly associated with education, the relationship is still significant and positive and an increase in numeracy skills by 20 points would require 0.54 additional education years when holding the literacy score constant. These figures are in line with other evidence from the literature that has approximated the education year equivalence of 20 PIAAC scores in cognitive skills to about one year of education (see e.g. Falck et al., 2016).

To express the skill distance between occupations in terms of education years necessary to acquire these skills, the coefficients of Table A1 col. 1 are used as weights for literacy and numeracy in equations (1) and (2). These weights ensure that the resulting skill differences are expressed in terms of the number of education years required to obtain the necessary cognitive skills enabling workers to move from occupation A to occupation B. The results of this analysis giving a first indication of the training needed to transition from one occupation to another are presented in Table A2.

Measuring occupation differences in terms of task-based skills

To evaluate the distance between occupations in terms of their requirements in task-based skills, this study relies on the five task-based skill indicators proposed in Grundke et al. (2017) and presented in Table 1, namely: ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills as well as self-organisation skills. For a hypothetical move from occupation A to occupation B, the following two equations (4) and (5) are used to calculate the shortage and the excess measures for the task-based skills, with the skill scores have been standardised across countries:

$$Shortage_{AB} = \sum_{t=1}^{5} w_t (score_B^t - score_A^t) I(score_B^t > score_A^t) \qquad (4)$$

$$Excess_{AB} = \sum_{t=1}^{5} w_t (score_A^t - score_B^t) I(score_B^t < score_A^t) \qquad (5)$$

Whereby $t \in$ (ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills, self-organisation skills) and *score* is the average score of the task-based skill t for occupation A or B (across 31 countries).

As for the occupation distances in terms of cognitive skills, the weights (w_t) for the shortage and excess measures for task-based skills are constructed based on the relative importance of the task-based skills in the destination occupation B. The task-based skill with the highest average score in occupation B receives a weight equal to 1. The weights for the other task-based skills are then computed by dividing the average score for the respective skill in occupation B by the average score of the task-based skill with the highest average score. This weighting method is an ad hoc choice and other alternative weighting methods might be used. However, weighting skill differences on the basis of the importance of the respective skills in the destination occupation B is sensible, as for workers moving from occupation A to occupation B it is most important to improve their competencies in the skills that are used most intensively in the new occupation.

For the task-based skills the equivalence of the skill distance in formal education years necessary to acquire these skills is not computed. The reason is that the schooling requirements equation would not be correctly specified because primary, secondary and tertiary education are more related to general cognitive skills and to a lesser extent to task-specific skills, which are mainly acquired and/or transmitted through learning-on-the-job. Therefore, the training needs related to the task-based skills required to move from an occupation A to an occupation B cannot be inferred using the methodology by Nedelkoska et al. (2015).

Conducting the analysis for subsets of countries

So far, this study has analysed occupation distances using the average skill requirements within 3 digit ISCO-08 occupation categories across all 31 countries. Doing so it has implicitly assumed that within three digit occupation categories no major differences in terms of skill requirements and task-contents exist across countries. However, as countries might considerably differ in their occupational skill requirements, the analysis is also conducted on four subsets of countries, which are similar with respect to their occupational skill requirements.

To this end a set of cluster analyses have been conducted to determine clusters of countries which are similar regarding the distribution of the task-based skill requirements within one digit ISCO-08 occupations. For the cluster analyses, the Euclidean distances between countries have been computed using the 25th, 50th and 75th percentile of each of the distributions of all five task-based skills within each of the nine ISCO-08 one digit occupations (in sum, 135 variables). In addition, the moments of the task-based skill distributions are weighted by the relative importance of the respective task-based skill within the one digit occupation considered (across countries), so as to give distances in those skills a greater weight, given that they are relatively more important for the occupation. Regardless of the specific type of cluster analysis implemented, the four country clusters shown in Table A3 are found to be robust, indicating that countries in each cluster display similar occupational skill requirements.

When conducting a hierarchical cluster analysis using the average linkage method, the cluster tree shown in Fig. A1 emerges. The first cluster comprises a group of Anglo-Saxon countries, namely Australia, Canada, the United States, Great Britain, New Zealand and Ireland. A second, slightly more heterogeneous cluster is the second cluster which includes Spain, Israel, Estonia, Poland, Slovenia, France, Singapore and Korea. The third cluster consists of the Nordic countries Denmark, Norway and Sweden as well as Germany, Austria, Belgium and the Netherlands. The fourth cluster is very small and includes Finland and the Czech Republic. The fifth cluster includes Chile, Greece, Italy, Turkey, Russia, Lithuania and Slovakia. These country clusters emerge independently of: using a different method to compute the minimum distance between countries and country clusters (weighted average linkage or single linkage method); using standardised or non-standardised variables; weighting the different moments of the skill distributions by the relative importance of skills in the occupation (or not); and using only the 50th percentile as single moment to characterise the distribution (compared to using all three moments).

Furthermore, several partitioning cluster analyses were used to determine the allocation of countries to clusters, with the number of clusters being determined ex-ante. However the number of clusters to be considered can also be inferred using a stopping rule. For the available stopping rules in Stata (the statistical package used for the purpose), the indicated number of clusters is 4 or 5. Specifying 4 clusters gives the same cluster structure of countries as shown in Table A3. When 5 clusters are specified, the cluster 1 in Table A3 splits into two groups. Interestingly, irrespective of specifying 4 or 5 clusters, Finland and Czech Republic always enter the same cluster of the Nordic countries Denmark, Norway and Sweden as well as Germany, Austria, Belgium and the Netherlands. These cluster patterns emerge independently of using different starting values for the cluster algorithm, of whether using standardised or non-standardises variables, of weighting the different moments of the skill distributions by the relative importance of skills in the occupation (or not) and using only the 50th percentile as single moment to characterise the distribution (compared to using all three moments).

Despite Finland and the Czech Republic emerging as a separate cluster in Fig. A1, since they only comprise around 8 000 observations (Table A3), the occupation distance analysis cannot be conducted for these countries alone. However, as the partitioning cluster analysis allocates them to the same cluster of Denmark, Norway, Sweden, Germany, Austria, Belgium and the Netherlands, they are allocated to cluster 3 in Table A3.

Including the readiness to learn of workers in the analysis

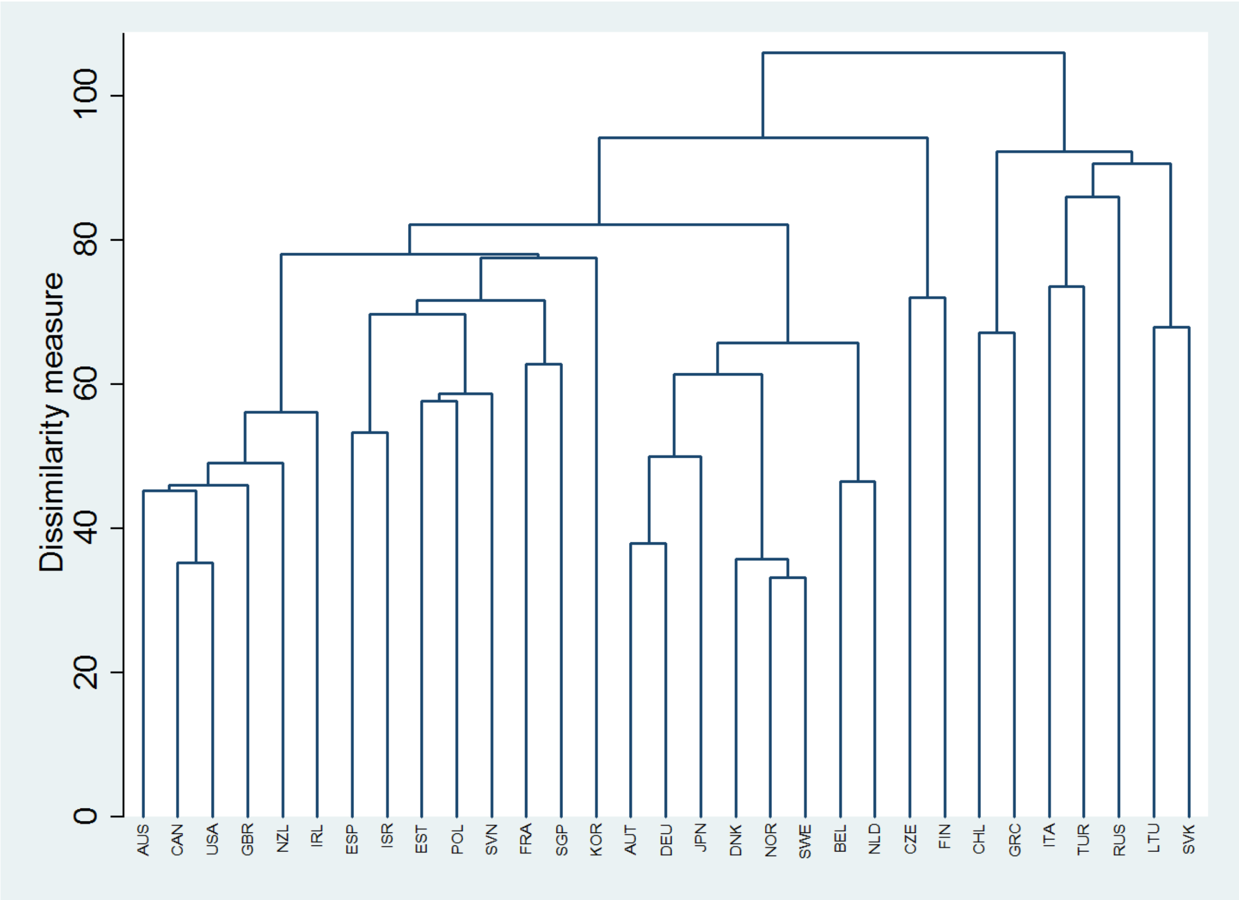
Because the ability of workers to move between occupations might also depend on workers' readiness to learn, additional analyses includes a measure of the readiness to learn and creative thinking of workers when computing skill distances between occupations (Table 1). The measure is based on individual self-assessment in PIAAC and is constructed as explained in Grundke, Jamet, Kalamova, Keslair and Squicciarini (2017). As a general readiness to learn is arguably important for upgrading all types of skills, cognitive and task-based skills, readiness to learn is included in the computation of occupation distances in terms of both sets of skills.

To include readiness to learn in the cognitive skill matrix, the measure was rescaled to the 0-500 interval. For each possible occupational move and in both skill distance measures, i.e. shortage and excess, readiness to learn's weight was set to be the average of the weights for literacy and numeracy. This was done to leave the weights for literacy and numeracy unchanged and to enable a comparison of the matrix including readiness to learn with the baseline matrix, which only includes literacy and numeracy.

For the inclusion of the measure for readiness to learn in the task-based skill matrix, the measure was standardised across countries. For each possible occupational move and in both skill distance measures, i.e. shortage and excess, the weight for readiness to learn was set to be the average of the weights for the other task-based skills. This again leaves the weights of the other skills unchanged and enables a comparison of the matrix including readiness to learn with the baseline matrix.

Figures and Tables

Figure A1. Cluster tree resulting from a hierarchical cluster analysis of countries



Note: The figure shows a cluster tree resulting from an average linkage hierarchical cluster analysis that uses the Euclidean distance between countries with respect to the following variables: the 25th, 50th and 75th percentile of the distribution of all five task-based skills within each of the nine ISCO-08 one digit occupations. It thus indicates similarities between countries in terms of the distribution of the task-based skill requirements within one digit ISCO-08 occupations. The links between countries are depicted through connecting lines, which represent the hierarchical structure of the clustering. The y-axis gives the degree of dissimilarities between countries or clusters of countries.
Source: Authors' own calculations based on the PIAAC data base.

Table A1. Regression of average education years and non-formal training on average skill variables (averages computed for each occupation category)

	(1)	(2)
Dependent variable:	Average years of schooling during lifetime	Average years of schooling during lifetime plus non-formal training in the current job
Average Literacy Score	0.056***	0.062***
	(0.016)	(0.018)
Average Numeracy Score	0.027**	0.026*
	(0.013)	(0.016)
Observations	127	127
Rsquared	0.831	0.815

Note: Column (1) shows the results of a simple OLS regression of the dependent variable average years of schooling (of workers in an occupation) on the independent variables average literacy and numeracy scores (of workers in the occupation). The sample comprises the 127 three digit ISCO-08 occupations included in the analysis. Column (2) presents the results for the same type of regression, but using as the dependent variable the average of the sum of years of schooling and non-formal training received in the current job (of workers in an occupation). Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own calculations based on the PIAAC data base.

Table A2. Occupation Distances in terms of cognitive skills (in education years)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	0.0	0.0	0.0	0.4	0.0
Keyboard operators	0.8	0.0	0.6	0.5	0.0	1.2	0.6
Tellers, money collectors and related clerks	0.2	0.0	0.0	0.0	0.0	0.6	0.0
Client information workers	0.4	0.0	0.2	0.0	0.0	0.7	0.2
Numerical clerks	0.8	0.0	0.6	0.5	0.0	1.2	0.6
Material-recording and transport clerks	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Other clerical support workers	0.2	0.0	0.0	0.0	0.0	0.6	0.0

Note: The Table shows an extract from the occupation distance matrix calculated using the cognitive skills literacy and numeracy, with the skill distance expressed in education years necessary to acquire these skills (using the coefficients presented in Table A1 column 1 as weights for the shortage and excess measures). The original symmetric matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage (1) and excess (2) are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column).

Source: Authors' own calculations based on the PIAAC data base.

Table A3. Clustering of countries

Country	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total Observations
AUS	0	5 603	0	0	5 603
AUT	0	0	3 734	0	3 734
BEL	0	0	3 385	0	3 385
CAN	0	19 675	0	0	19 675
CHL	3 620	0	0	0	3 620
CZE	0	0	3 673	0	3 673
DEU	0	0	4 068	0	4 068
DNK	0	0	5 334	0	5 334
ESP	0	0	0	3 386	3 386
EST	0	0	0	5 391	5 391
FIN	0	0	3 885	0	3 885
FRA	0	0	0	4 518	4 518
GBR	0	5 910	0	0	5 910
GRC	2 463	0	0	0	2 463
IRL	0	3 677	0	0	3 677
ISR	0	0	0	3 659	3 659
ITA	2 869	0	0	0	2 869
JPN	0	0	3 881	0	3 881
KOR	0	0	0	4 428	4 428
LTU	3 218	0	0	0	3 218
NLD	0	0	3 943	0	3 943
NOR	0	0	3 955	0	3 955
NZL	0	4 538	0	0	4 538
POL	0	0	0	5 152	5 152
RUS	2 242	0	0	0	2 242
SGP	0	0	0	3 989	3 989
SVK	3 319	0	0	0	3 319
SVN	0	0	0	3 019	3 019
SWE	0	0	3 354	0	3 354
TUR	2 318	0	0	0	2 318
USA	0	3 560	0	0	3 560
Total	20 049	42 963	39 212	33 542	135 766

Note: The table shows the allocation of countries to clusters resulting from a cluster analysis grouping together countries with similar distributions of task-based skills within ISCO-08 1 digit occupations.
Source: Authors' own calculations based on the PIAAC data base.

Table A4. Occupation distances in terms of cognitive skills (country cluster 1)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	0.0	6.5	7.5	14.8	16.0
Keyboard operators	30.1	0.0	19.1	36.6	37.6	44.9	46.1
Tellers, money collectors and related clerks	11.1	0.0	0.0	17.7	18.6	26.0	27.3
Client information workers	0.0	0.0	0.0	0.0	4.1	8.3	9.5
Numerical clerks	0.0	0.0	0.0	3.2	0.0	7.4	8.7
Material-recording and transport clerks	0.0	0.0	0.0	0.0	0.0	0.0	2.7
Other clerical support workers	0.0	0.0	0.0	0.0	0.0	1.4	0.0

Note: The Table shows an extract from the occupation distance matrix computed for the subsample of countries including Chile, Greece, Italy, Turkey, Russia, Lithuania and Slovakia. The matrix was calculated using the cognitive skills literacy and numeracy, with the scale for PIAAC cognitive skill scores ranging between 0-500. The original matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures were calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table A5. Occupation distances in terms of cognitive skills (country cluster 2)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	3.6	0.0	0.0	26.0	0.0
Keyboard operators	6.6	0.0	8.5	5.4	0.0	32.8	2.0
Tellers, money collectors and related clerks	1.7	0.0	0.0	1.4	0.0	24.3	0.0
Client information workers	2.1	0.9	5.4	0.0	0.0	28.0	1.5
Numerical clerks	14.7	8.1	16.6	12.6	0.0	40.7	10.2
Material-recording and transport clerks	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other clerical support workers	4.6	0.0	6.5	4.0	0.0	30.7	0.0

Note: The Table shows an extract from the occupation distance matrix computed for the subsample of countries including Australia, Canada, the United States, Great Britain, New Zealand and Ireland. The matrix was calculated using the cognitive skills literacy and numeracy, with the scale for PIAAC cognitive skill scores ranging between 0-500. The original matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures were calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table A6. Occupation distances in terms of cognitive skills (country cluster 3)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	0.0	0.0	0.0	6.3	0.3
Keyboard operators	20.3	0.0	3.7	8.3	0.0	26.5	20.5
Tellers, money collectors and related clerks	16.6	0.0	0.0	4.6	0.0	22.8	16.8
Client information workers	12.0	0.0	0.0	0.0	0.0	18.2	12.2
Numerical clerks	26.3	5.9	9.7	14.3	0.0	32.6	26.5
Material-recording and transport clerks	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other clerical support workers	0.1	0.0	0.0	0.0	0.0	6.1	0.0

Note: The Table shows an extract from the occupation distance matrix computed for the subsample of countries including Denmark, Norway and Sweden as well as Germany, Austria, Belgium and the Netherlands. The matrix was calculated using the cognitive skills literacy and numeracy, with the scale for PIAAC cognitive skill scores ranging between 0-500. The original matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures were calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table A7. Occupation distances in terms of cognitive skills (country cluster 4)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Keyboard operators	41.7	0.0	33.2	23.3	13.5	31.0	17.0
Tellers, money collectors and related clerks	8.6	0.0	0.0	0.0	0.0	0.1	0.0
Client information workers	18.4	0.0	9.9	0.0	0.0	7.7	0.0
Numerical clerks	28.3	0.0	19.8	9.9	0.0	17.6	3.5
Material-recording and transport clerks	10.9	0.0	2.4	0.0	0.0	0.0	0.0
Other clerical support workers	24.9	0.0	16.3	6.4	0.0	14.1	0.0

Note: The Table shows an extract from the occupation distance matrix computed for the subsample of countries including Spain, Israel, Estonia, Poland, Slovenia, France, Singapore and Korea. The matrix was calculated using the cognitive skills literacy and numeracy, with the scale for PIAAC cognitive skill scores ranging between0-500. The original matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures were calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table A8. Occupation distances in terms of cognitive skills (including readiness to learn)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	2.0	0.0	0.0	3.4	12.2	3.0
Keyboard operators	20.3	0.0	14.6	12.1	2.1	28.8	15.5
Tellers, money collectors and related clerks	6.9	3.1	0.0	1.2	4.6	17.4	4.1
Client information workers	9.4	3.2	3.8	0.0	4.7	19.9	7.8
Numerical clerks	21.2	1.4	15.4	12.9	0.0	28.2	15.2
Material-recording and transport clerks	1.8	0.0	0.0	0.0	0.0	0.0	0.0
Other clerical support workers	5.9	0.0	0.1	1.2	0.4	13.4	0.0

Note: The Table shows an extract from the occupation distance matrix calculated using the cognitive skills literacy and numeracy, with the scale for PIAAC cognitive skill scores ranging between 0-500, as well as an indicator for readiness to learn which was rescaled to the 0-500 interval. The original matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the skill shortage and excess measures were calculated based on the relative importance of skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

Table A9. Occupation distances in terms of five task-based skills (including readiness to learn)

	Secretaries (general)	Keyboard operators	Tellers, money collectors and related clerks	Client information workers	Numerical clerks	Material-recording and transport clerks	Other clerical support workers
Secretaries (general)	0.0	2.0	0.9	0.9	0.2	1.1	1.1
Keyboard operators	0.0	0.0	0.2	0.0	0.1	0.4	0.2
Tellers, money collectors and related clerks	1.0	2.6	0.0	0.9	0.8	1.5	1.5
Client information workers	0.3	1.6	0.2	0.0	0.6	0.8	0.7
Numerical clerks	0.9	2.9	1.3	1.8	0.0	1.8	1.9
Material-recording and transport clerks	0.2	1.8	0.5	0.5	0.3	0.0	0.3
Other clerical support workers	0.1	1.4	0.3	0.3	0.3	0.2	0.0

Note: The table presents an extract of the occupation distance matrix calculated using the five task-based skills as well as an indicator for readiness to learn. The task-based skills and the indicator for readiness to learn are standardised across countries so that the standardised skill scores have mean zero and standard deviation equal to 1. The symmetric matrix includes 127 three digit ISCO-08 occupations (i.e. it has 127 rows and 127 columns). For each occupation pair, the two measures for shortage and excess are calculated and included in the matrix. The shortage measure is presented for a move from the column occupation to the row occupation, the excess measure for a move from the row occupation to the column occupation. For a specific pair of occupations A and B, the shortage measure for a move from A to B (column to row) equals the excess measure for a move from B to A (row to column). The weights for the shortage and excess measures were calculated based on the relative importance of task-based skills in the destination occupation and origin occupation, respectively.
Source: Authors' own calculations based on the PIAAC data base.

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Notes

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[2] http://www.oecd.org/skills/piaac/.

[3] Using German data: Gathmann and Schoenberg, 2010; Nedelkoska et al., 2015. Using data on the United States: Poletaev and Robinson, 2008. Most papers rely on either U.S. O*NET data (or its predecessor, the U.S. Dictionary of Occupational Title) or German Qualification and Career Survey which characterise occupations by their content in terms of tasks or skills.

[4] In few cases, country-specific surveys like O*NET for the United States may be used to look at the skill and task content of occupations in detail and to obtain additional insights on workers' training needs. Such country-specific data may further help shedding extra light on the role of occupation-specific knowledge areas. However, only PIAAC provides comparable country-specific information for 31 countries.

[5] Ongoing work is using PIAAC information on workers' field of study to proxy differences in specific knowledge areas between occupations. Also, occupational skill distances are further calculated for clusters of countries, to uncover possible country specificities in occupational skill and task contents.

[6] This is similar to the analysis in Poletaev and Robinson, 2008; Gathmann and Schoenberg, 2010.

[7] In contrast to most papers in the task-specific human capital literature, Yamagushi (2012) does not treat tasks as proxies for unobserved workers' skills, but distinguishes between job tasks and worker skills.

[8] A number of studies provide evidence consistent with the predictions of this model, e.g. Katz and Murphy (1992); Acemoglu (1998); Autor, Katz, and Krueger (1998); Machin and Van Reenen (1998); Card and DiNardo (2002); Goldin and Katz (2008).

[9] The effect of technological change on the decrease of employment in occupations associated with high shares of routine tasks and labour market polarisation has been document by many recent empirical studies, including Acemoglu and Autor (2011); Autor and Dorn (2013); Autor (2015) and Acemoglu and Restrepo (2016).

[10] An assumption which is not as unrealistic according to Handel (2012) who finds that country specificities play a minor role in explaining differences in skill requirements of occupations.

[11] The third cognitive skill measured in PIAAC, problem solving in technology-rich environments, is included in the analysis in robustness checks. The reason for not including this measure in the baseline analysis is that many individuals with generally lower literacy and numeracy skills did not take the assessment test for problem solving (OECD 2016b). Excluding these individuals from the analysis would lead to a strong selection bias. Also, France, Italy and Spain have not participated in the assessment tests for problem solving and would be excluded from the analysis when using problem solving as a third cognitive skill.

[12] To this end the weighted mean and standard deviation for each task-based skill indicator have been computed for the pooled sample using final sample weights.

[13] The costs related to (re)training workers to gain the necessary task-based skill to move from any occupation A to an occupation B cannot be inferred using the methodology by Nedelkoska et al. (2015).

[14] Occupation(s) refers to 3-digit level occupations of the 2008 International Standard Classification of Occupations (ISCO-08).

[15] Occupations group(s)" or "group(s) of occupations" refer to 1-digit ISCO-08 occupations.

[16] If problem solving is included in the analysis, the sample size is reduced from 127,853 to 92,357 individuals.

[17] Results are not shown but can be obtained from the authors.

[18] The occupations in the armed forces (starting with the first digit 0) as well as all occupations with less than 5 observations are excluded from the analysis.

[19] The PIAAC survey is a representative survey for each of the participating countries and includes final sample weights for each individual. These sample weights are calculated based on the country-specific survey and sampling design (OECD 2016).

[20] In robustness checks the analysis was conducted using so-called senate weights, which give each country the same weight in the analysis. The main results do not change and can be obtained from the authors upon request.

[21] Nedelkoska et al. (2015) call this measure redundancy. To avoid any negative connotation for an occupational move whereby the worker is endowed with a higher level (for some skills) than needed for the new job, this study calls the measure skill excess.

[22] This variable is included in the PIAAC data set. In a robustness check, the highest level of education obtained by the individual (imputed into years of education) was used as dependent variable and results do not change. In a second regression, years of formal education are augmented by new measures on the time spent in informal training during working time based on the work of Squicciarini et al. (2015) and results do not change (Table A1).