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UNTANGLING LABOUR SHORTAGES IN EUROPE: UNMET SKILL DEMAND OR BAD JOBS?

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Contents

Tables, figures and boxes

Tables

Figures

Boxes

Abstract

Based on unique data from the second wave of the Cedefop European skills and jobs survey (ESJS2), this study examines the drivers of labour shortages in European labour markets. Detailed information on foundation, digital, manual, and interpersonal job-skill requirements in European labour markets, collected through the ESJS2 at job rather than occupation level, is first exploited to construct robust and comprehensive indices of the required skills profile of European jobs. These measures are subsequently used to investigate to what extent occupational labour shortages are underpinned by high(er) skill demands as opposed to other drivers (including labour market immobility, worker skills gaps, unattractive working conditions). The evidence reveals significant variance in the underlying determinants of labour shortages across occupations, highlighting the fallacy of one-size-fits all policies. Occupations in bottleneck are generally underpinned by low cognitive skill needs but high demands for learning and adaptability on behalf of workers. In some occupations shortages may be best tackled through the improvement of job quality or reduction in labour turnover.

Introduction

The COVID-19 pandemic, the war in Ukraine and the wider social turmoil that have affected the post-pandemic ‘perma-crisis’ era, have accentuated labour and skill shortages across Europe and the global economy (Pouliakas and Wruuck, 2022; European Commission, 2023; Cedefop, 2023). Although excess labour demand largely reflects cyclical drivers, long-standing labour market mega-trends, including the rapid diffusion of new digital technologies and working modes accelerated by the pandemic (Cedefop, 2022a,b), together with growing labour market inactivity and population ageing (Cedefop, 2023), may also result in persistent skill mismatches, with economic costs and labour market inefficiencies (Pouliakas, 2012; McGuinness et al., 2018). Pouliakas and Wruuck (2022) have demonstrated that the COVID-19 pandemic reversed the upward trend in company training investments of in the pre-pandemic period, exacerbating prior inequalities in training provision and causing a wedge between them and skill shortages.

Shortages of workers at varying skill levels typically occur when demand may exceed available supply, given prevailing market wages and available working conditions (Shah and Burke, 2005; Cedefop, 2010, 2015a, b). There is ambiguity in available literature in defining the phenomenon, with many reports referring to ‘skill shortages/gaps’ as a catch-all term (Cappelli, 2015). Scholars have recently aimed, however, to make a clearer distinction between situations whereby employer vacancies are hard to fill due to distinct factors: an overall lack of a readily available workforce; poor human resource management (HRM) practices; low quality job offers; or qualification and skill deficiencies among job applicants (Box 1). Clearly differentiating ‘labour shortages’ (also commonly referred to as ‘quantitative labour imbalances’, ‘recruitment bottlenecks’ or ‘hard-to-fill vacancies’) from ‘skill shortages’ (or ‘qualitative labour imbalances’) is a challenging endeavour (Green et al., 1998). It is, however, crucial for accurately underpinning the most appropriate policy remedy: one of expanding vocational education and training (VET) investments, as opposed to prioritising other activation (e.g. job search, career guidance), workforce recruitment or other related (e.g. migration) policies (Sattinger, 2012).

Designing targeted initial or continuing VET interventions becomes necessary when vacancies cannot be filled because there is an absence of suitable job applicants with the desired qualifications, skills or related work experience (UKCES, 2010). When training times needed to develop the required skills are long, the impact of such complex skill shortages on the productivity and innovative capability of firms may be significant (McGuinness et al., 2018; Bennett and McGuinness, 2009; Haskel and Martin, 1993). Such ‘skill shortage vacancies’ usually constitute a subset of companies’ overall recruitment difficulties (Cedefop, 2015a).

Box 1. **Definitions of skill shortages**

Labour market (skill) imbalances	**A difference between the aggregate quantities of demand and supply of individuals (with different skill levels) in an economy.**
Labour market mismatch	A situation where the unemployment to vacancy ratio across different industries, occupations, localities or skill groups, diverges from the average ratio in the economy over time.
Labour shortage	A situation in which the demand for labour exceeds the supply of available people. A situation where a given vacancy (posted in a recent time period) is hard to fill by employers – a.k.a. 'recruitment bottleneck' / 'hard-to-fill vacancies'.
Skill shortage	A situation when there are not enough individuals with the required skills within the economy, to fill existing vacancies under prevailing market wages and working conditions (and within a reasonable location) (Shah and Burke, 2003; Cedefop, 2010; Barnow et al., 2013; Australian government, 2022). More refined definitions have been proposed to incorporate training lead time (Richardson, 2007), dynamic interactions between skill demand and supply (Arrow and Capron, 1959), the complexity of a vacancy (Healy et al., 2015), the time it takes for a shortage to clear in reaction to market signals and other important elements (Cedefop, 2015a). The UK Employer skills survey typically refers to a 'skills-shortage vacancy' as one that is hard to fill because of the absence of suitable job candidates with right qualifications, skills or relevant work experience.

Source: Cedefop (2010, 2015a); Lazear and Spletzer (2012).

Most available research has struggled to determine clearly if (occupational) shortages are associated with greater or changing skill demands, or reflect inferior recruitment practices or bad working conditions, inability for market wage clearing or other labour market failures. This is typically the case because of a lack of direct measures of skill needs in labour markets, as well as other job quality indicators, at detailed occupational level. While most previous studies have relied on indirect, broad proxies of job-skill requirements (e.g. International Standard Classification of Occupations (ISCO) classifications, mean education or wage level per occupation), Handel (2003) has argued that 'real progress on the question of skills mismatch requires development of a new, validated, standardized method of measuring job skill demands administered consistently to representative samples of workers over time to understand exactly in what ways work is changing'. Precise and comparable measures of job-skill requirements would allow researchers to study specific skill needs and their evolution over time.

To overcome this deficiency, this study exploits new, robust, and internationally comparable data drawn from Cedefop's second European skills and jobs survey (ESJS2) (Box 2). Using a now well-established task-based approach to surveying adult workers (Spitz-Oener, 2006; Green et al., 2012; Handel, 2016), the ESJS2 dataset contains novel information to depict the cognitive and non-cognitive job-skill requirements of European jobs. These data are coupled with other suitable ESJS2 job quality factors to enable an in-depth investigation of the extent to which labour shortages in European economies may be attributed to growing skill needs or other job quality features.

Box 2. **In brief: Cedefop's second European skills and jobs survey (ESJS2)**

The ESJS2 is the second wave of a Cedefop periodic survey collecting information on the job-skill requirements, digitalisation, skill mismatches and workplace learning of representative samples of European adult workers. It builds on the first wave carried out in 2014 and aims to inform the policy debate on the impact of digitalisation on the future of work and skills, also in the context of the COVID-19 pandemic.

Fielded in summer 2021, the ESJS2 collected information about 46 213 adult workers in the EU-27 Member States plus Norway and Iceland (EU+). As Cedefop has joined forces with the European Training Foundation (ETF), by 2023, the ESJS2 had been carried out in more than 35 EU and EU periphery countries.

The ESJS2 collects complete information on the socio-demographic and job profile of EU+ adult workers. It maps the task structure of EU+ jobs and uses it to proxy job-skill requirements in labour markets. The focus is on literacy (reading, writing), numeracy, physical, interpersonal, and problem-solving tasks, along with digital activities carried out at work and the incidence and impact of technological change for work. ESJS2 also collects information characterising the nature of work and its organisation (e.g. routine, autonomous, standardised, learning-intensive). The extent to which skill mismatches affect digital and overall productivity at work and efforts to mitigate them via education and training, is also measured.

The ESJS2 aspires to become a key tool for evidence-based policymaking in VET. Its design incorporates the growth, sustainability and resilience ambitions of the EU Skills Agenda and European Digital Strategy and acknowledges the importance of digital skills in VET put forward in the 2020 Council Recommendation on VET and the Osnabrück Declaration.

More information on the European skills and jobs survey (ESJS) is available on Cedefop's web portal and data access is provided via the dedicated ESJS2 online tool.

Source: Cedefop.

The remainder of this paper is structured as follows. Chapter 2 provides a brief overview of the available literature on labour and skill shortages. It also reviews available research that has aimed to measure the nature of skill demands in economies using specific, task-based approaches. Chapter 3 presents some descriptive statistics showcasing the variation in skill demands and labour shortages across European job markets. Chapter 4 demonstrates the outcomes of a multivariate regression analysis that aims to estimate the probability of workers belonging to labour shortage occupations and discusses its underlying determinants. Chapter 5 concludes.

SECTION 1.
Skill demands and shortages

1.1. Drivers of labour and skill shortages

Difficulties in finding employees with the required skills to fill their vacancies is an often-reported obstacle faced by European firms (Pouliakas and Wruuck, 2022; Brunello and Wruuck, 2021).

Concerns about the existence of labour and skill shortages in an economy are important, as they can constitute a significant impediment to firms' productivity and competitiveness and can constrain their ability to remain at the top of the technological frontier (Healy et al., 2015; Bennet and McGuinness, 2009; Forth and Mason, 2006; Nickell and Nicolitsas, 1997; Haskel and Martin, 1993; Brunello and Wruuck, 2021). While several economists claim that shortages in perfectly competitive labour markets are not sustainable, given that market-clearing forces will eventually restore equilibrium between labour demand and supply, several factors may sustain inefficiency in the matching process between available job candidates (if they exist) and vacancies.

Boswell et al. (2004) summarise such explanations for the persistence of skill shortages under four broad groupings: qualitative / skill mismatches; geographic mismatches; preference mismatches; and information mismatches. Specifically, reasons for labour shortages/inability to fill vacancies may be: overall absence of enough people due to demographic or mobility constraints (lack of people); absence of (available) job candidates with the rights skills, knowledge and experience required for the job (lack of skills); information asymmetries (lack of information); behavioural choices (e.g. poor recruitment practices used by firms; insufficient search intensity of job seekers) inhibiting the efficient matching of existing skill supply with demand (lack of effort); or unattractive job offers characterised by low pay or bad working conditions that do not satisfy individuals' reservation wages (lack of good jobs). It is therefore evident that, from a policy perspective, there may be many different remedies to be followed depending on the underlying cause of the shortage.

Long-term technological and demographic forces are often seen as drivers of rapidly changing labour demand and supply (Cedefop, 2023). A failure of education and training systems to provide young graduates with the skills required in contemporary job markets is another reason mentioned in several policy reports (Handel, 2003). Underinvestment in (general) training due to market failures such as poaching externalities (Becker, 1967; Mincer, 1974), capital market imperfections, monopsonistic labour markets (Stevens, 1994; Acemoglu and Pischke, 1999) and coordination failures fostering low-skill/low-innovation equilibria (Redding, 1996), are often highlighted as further reasons for lagging skill supply among incumbent workers that may breed shortages (Almeida et al, 2012). Skill shortages may also arise due to institutional constraints inhibiting labour market mobility (e.g. rigid wage systems or employment protection legislation), in addition to other geographic segmentation or congestion effects.

Information asymmetries regarding the qualities of jobs and/or job applicants, and the heterogeneity in individuals' job preferences, such as reservation wages that cannot be overcome by the wage and working conditions on offer, are additional culprits. Variation in recruitment and HRM practices at firm level (Cappelli, 2015) may further sustain shortages by failing to attract or retain labour reserves, confounding labour turnover difficulties with labour shortages.

1.2. Measuring job-skill requirements

A common thread joining the above theories of why labour shortages may occur, is the presumption of high and accelerating skill demands, which outpaces skill supply. This has often been the case in several research and policy reports, even though such claims typically rely on broad (occupational) proxies of skill demand in economies. To understand if labour/skill shortages mostly arise because of high skill needs, as opposed to other factors, it is necessary to have a reliable measure of skill needs that also includes their within-occupation variability.

As explained by Lazear (2009), according to the 'skill-weight' approach, the skills required in firms can be too general, and hence not truly 'firm-specific'. However, they can be acquired and used in relatively idiosyncratic patterns; this makes the weights associated to skills demanded different across firms. This has consequences for the cost that firms must bear in training workers in specific skills or in experiencing high turnover and displacement. A clear measurement of job-skill requirements can help shed light on firms' training decisions. In addition, the variability of skills required by firms for a given 'shortage' occupation may underpin corporate recruitment challenges. The relevance of this hypothesis can be assessed by studying the distributions of skill demands within given occupation categories.

Obtaining a specific measure of job-skill requirements and exploring their relationship to technology and work organisation has received increasing attention in recent years in various research fields, ranging from labour and education economics to sociology. Many important labour market phenomena, including wage development and inequality, job mobility, transition from school to work and skill shortages, hinge on a better understanding of the nature and trend of skill needs in economies. Following the outbreak of the COVID-19 pandemic, data sources capturing the task content of jobs were extensively used to study the potential for teleworking in occupations (see Flisi and Santangelo, 2022 for a review). This type of analysis is also critical for evidence-based policy recommendations, since it can provide insight into the possible drivers of firms' recruitment challenges: for example, is it necessary to aim to stimulate skill supply through worker upskilling or are other labour demand policies more suitable.

Despite the long-standing relevance of the topic, the conceptual basis for measuring job-skill requirements / job tasks, has only recently become mainstream in labour economics (Handel, 2016, 2020). In the past, most studies used rough proxy measures of job-skill demands available in nationally representative data sets and based on broad occupational groups; these included grouped international standard classification of occupations (ISCO) categories, or mean education or wage level by occupation. Other researchers have relied on average task intensity measures at occupation-level obtained from occupational experts or small samples of incumbent workers. Case-level measures created for unique surveys administered to restricted samples and unstandardised interview methods for qualitative case studies, have also been deployed (Bartel et al., 2007).

Many studies have relied in the past on the U.S. Dictionary of occupational titles (DOT), replaced in 2000 by the Occupational information network (O*NET). While the DOT was based on numerical skill scores produced by trained raters through site visits to workers, supervisors and managers, the O*NET relies on both expert inputs and incumbent worker surveys. Both databases cover many dimensions of job requirements, but contain mean skill ratings by detailed occupation, hence precluding the analysis of changes in job content within detailed occupations.

For Europe, a database closely replicating O*NET, although with some methodological differences, is the *Indagine Campionaria sulle Professioni* (ICP), developed by the Italian National Institute for Public Policy Analysis (INAPP) and the Italian National Statistical Institute (ISTAT). It is referenced to the Italian occupational structure and is based on survey evidence collected at worker level that is validated ex-post by experts.

Handel (2016, 2020) is the first to have developed and used the information from the US survey of Skills, technology, and management practices (STAMP), a forerunner to the ESJS2, to analyse the levels and trends of skills, computer use and employee involvement practices. He also studied the interrelationships among these aspects and their effect on wages, working conditions and job characteristics. He found that job-skill requirements and cognitive skill demands in the US job market are low to moderate, and that information technology is used widely but generally at low to moderate levels of complexity. He also showed that many workers report personal education levels that exceed those required by their job.

The availability of homogeneous and comparable measures of job-skill requirements in Europe has been scarce until lately. Some data on job tasks has been collected as part of the long-standing British skills and employment survey (SES), which has now been administered in seven waves between 1986 and 2017 and used by Felstead et al. (2007) and Green et al. (2016) to study job characteristics and skills in the UK.

In Germany, the Qualification and career survey, conducted by the German Federal Institute for Vocational Training (*Bundesinstitut für Berufsbildung*, BIBB) and the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*, IAB) between 1979 and 2018, covers a wide range of topics. This includes job-skill requirements and tasks, plus detailed information on the tools and machines used at the workplace, with a focus on computers, terminals, and electronic data-processing machines. Building on the STAMP survey, Matthes et al. (2014) used the German National educational panel study (NEPS) to measure job tasks, but exclusively for the German labour market. They highlighted the importance of actual task measures and their utility in analysing changes in the overall structure of the economy, as well as their implications for both persons and firms, for instance on wage developments. They distinguished between five major types of task: analytic, interactive, manual, routine, and autonomy-demanding. They further defined routine tasks over two main dimensions: task complexity and organisational aspects relating to worker autonomy.

Drawing from both the British SES and STAMP, the Organisation for Economic Co-operation and Development (OECD) Programme for the international assessment of adult competencies (PIAAC) international survey also measures key cognitive and workplace skills needed for individuals to work and participate in society (OECD, 2012). Although focused primarily on working conditions, Eurofound's periodic European working conditions survey (EWCS) contains some information on the learning requirements of EU jobs, skills, and work organisation.

In 2016, the EWCS was used by the European Commission's Joint Research Centre (JRC) and Eurofound, in combination with the O*NET and ICP, with the aim of developing a 'task-based' framework and database that could be used to provide insight into the structure of jobs in Europe. In this framework, job tasks are classified and measured along two main dimensions: the content of the tasks themselves and the methods and tools used to perform them. The content part, which is mainly related to what type of activities workers carry out at work, is clustered into three main domains related to physical, intellectual, and social tasks. Methods refer instead to the way that work is organised, for instance in terms of autonomy, teamwork, or work routinisation, while the tools capture the type of digital equipment or other machinery used to carry out tasks.

Building on the original European jobs monitor 2016 (Fernández-Macías, et al., 2016a, 2016b), Fernández-Macías and Bisello (2022) further developed a comprehensive taxonomy of tasks contents, methods and tools. They used a new set of indicators, connecting the substantive content of work with its organisational context, to analyse the distribution and evolution of the tasks of European workers, with a focus on the impact of new technologies on work. This taxonomy was then further updated and used in Bisello et al. (2021) to create an enriched version of the European database of task indices across jobs in the EU-15 ([1]) (minus UK). The analysis of tasks distribution across occupations and sectors at the European level was used to describe the work content and organisational methods prevailing along the employment structure, highlighting the complexity of work activities characterising single jobs.

In 2022 Eurostat developed an ad-hoc module as part of the European Union labour force survey (EU-LFS) focused on 'Job skills' ([2]). The purpose of this module is to collect data on the time spent by European workers on tasks requiring specific skills. This is done to fulfil the need for robust, representative, in-depth and comparable information on job-skill requirements across Europe.

Different measures used to assess skills and job tasks have their advantages and limitations. Occupational databases such as DOT, O*NET and the ICP are unquestionably more comprehensive than survey data since they cover the entire spectrum of the occupational structure at a high level of detail. However, they are limited in terms of their possibility to analyse the variability of tasks and skill demands within the same occupation and over time, as the data included in these databases are collected at the level of occupations rather than individual workers.

([1]) EU-15 minus UK: Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland and Sweden.

([2]) European labour force survey: overview of modules.

Surveys of workers conducted at regular intervals offer, by contrast, the potential for time series monitoring and analyses, provided there is repeated and consistent collection of job skill requirement measures. Such measures are based on workers' perceptions, leaving room for individual response biases, and the information on skills is typically collected at general or meta level to ensure relevance across all kinds of jobs ('generalisability'). To overcome these limitations, many efforts have been made in the construction of recent skills surveys (such as STAMP, UK SES and ESJS2) to improve the objectivity and interpretability of measures; they aim to offer a more systematic conceptualisation of the domain and survey questions anchored to clear and commonly understood rating scales and reference periods, so-called 'explicit scaling' (Handel, 2016; Cedefop, 2022a).

In recent years, the availability of information on skills demand based on information extracted from online job advertisements (OJAs) has marked an outstanding development for research in this field (Cedefop et al., 2021). Burning Glass/Lightcast data provided for the United States job market was a first example of such efforts, while Cedefop tested and built the Skills online vacancy analysis tool for Europe (Skills-OVATE), collecting data from all European countries starting in July 2018. Since then, and as part of the Web Intelligence Hub, Eurostat has been coordinating with Cedefop to ensure the provision of smart and trusted statistics on skills based on information available from the web ([3]).

OJAs offer highly granular information on employer demand for jobs and skills (e.g. at sector, occupation or regional level) through online job postings retrieved from thousands of web sources, including private job portals, public employment service portals, recruitment agencies, online newspapers and employers' websites. This means that OJAs have the potential to provide comprehensive, detailed, and timely (quasi real-time) insights into labour market and skill demand trends and may also help identify new and emerging jobs and skills, as for instance the growing importance of social or other cognitive or non-cognitive skills (Deming, 2017; Deming and Kahn, 2018).

However, as pointed out by Cedefop et al. (2021), data from OJAs present some limitations related to their representativeness, meaningfulness, and consistency over time and are prone to measurement errors. OJAs are likely to provide a biased representation of the structure of jobs in labour markets, missing out on jobs that are not posted online, such as those filled in internally or via other recruitment channels, or reflecting vacancies that are not meant to be filled (ghost vacancies). The penetration of the online recruitment market and employers' choice to use online portals as a recruitment channel vary within and across countries and over time. It is also dependent on internet penetration and digital skills across the population. OJAs are more likely to capture jobs at the higher end of the skills spectrum (e.g. information and communications technology (ICT) professions), which are more typically advertised via the web (Sostero et al., 2021). The skills captured via OJA analysis are also significantly heterogeneous, partial, and prone to systematic measurement (classification or clustering) errors. They also reflect employers' 'wants', akin to a contest intended on attracting suitable candidates, rather than actual skill demands of occupations. For most countries there is no single source for online jobs ads, and the volume, variety, and quality of the data depend

([3]) Web Intelligence Hub. Trusted smart statistics.

on the selected portals, which are often not consistent through time, leading to breaks in the time series. OJAs typically lack the substantive contextual background variables on workplaces, jobs and individual traits that are necessary for engaging in a scientific investigation of the determinants and dynamics of skill mismatches in labour markets, as that carried out in Cedefop (2015b, 2018, 2022b).

In the next section, we exploit detailed information on job-skill requirements obtained as part of Cedefop's second ESJS. This allows us to paint a profile of the skills required in European labour markets and subsequently to analyse their relationship with occupational labour shortages, alongside other factors.

SECTION 2.
Data and descriptive evidence

2.1. Cedefop's European skills and jobs survey

To fill in knowledge gaps in terms of job-skill requirements and skill mismatches at European level, between 2012-14 Cedefop developed the first European skills and jobs survey (ESJS). The ESJS data were used to explore in-depth the incidence and determinants of skill mismatches in EU labour markets in the aftermath of the great financial crisis, discussing related drivers and policy challenges and looking at the many different dimensions of skill mismatch (Cedefop, 2015b, 2018).

In 2021 Cedefop implemented a second wave of the survey (ESJS2), focusing on the changing skill needs and job tasks of EU workers, their relationship with digitalisation, and the adaptability of employees to technological change via their participation in VET and workplace learning (Cedefop, 2022a, 2022b) ([4]). The ESJS2 was designed to inform policy debate on the impact of new digital technologies and technological change on the future of work and skills, in the context of the COVID-19 pandemic and the ensuing spread of new forms of remote work and distance learning ([5]).

This second wave, collecting data from a sample of 46 213 adult employees from all EU Member States plus Norway and Iceland (henceforth EU+), collects complete information on the socio-demographic and job characteristics of EU+ adult workers, with emphasis on the level of skills complexity required and associated skill mismatches. It specifically measures the intensity of foundation skills (literacy, as in reading and writing, and numeracy), digital skills, interpersonal skills, problem-solving skills, and physical skills required in the jobs of adult workers (Cedefop, 2022b). It maps in detail the type of digital activities carried out at work and the incidence and impact of technological change for work. It does so by obtaining robust, comparable, and representative information from job holders, permitting comparisons of their skill demands in different industries and occupations, as well as offering insight into the within-occupational distribution of job-skill requirements. The ESJS2 contributes to the continuing task approach to measuring skill demands in economies; it also collects information characterising the nature of work and its organisation (e.g. routine, autonomous, standardised procedures, learning-intensive). The extent to which skill mismatches (vertical and horizontal qualification mismatches, skill gaps, skill utilisation) are evident at work, and efforts to mitigate them via continuing education and training, are further measured.

The up-to-date evidence provided by the ESJS2 on how digitalisation accelerated in EU labour markets during the coronavirus pandemic allows us to identify worker groups affected

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([4]) Through a collaboration between Cedefop and the European Training Foundation (ETF), the ESJS2 has also been carried out in six additional countries (Western Balkans and Israel) in 2022-23. The ESJS2 database contains information for 35 EU and EU-periphery countries.

([5]) Interested readers can access ESJS2 data and relevant breakdowns (e.g. country, sector, occupation, age, education) via the dedicated Cedefop online tool.

by task automation and digital skill gaps, specifically those in need of targeted upskilling or reskilling following the adoption of digital technology (Cedefop, 2022a, b).

2.2. Profiling job-skill requirements in EU+ labour markets

The relevant ESJS2 variables are used to construct robust scales of the following job-skill requirements ([6]):

(a) foundation job-skill requirements (literacy and numeracy);
(b) social/interpersonal job-skill requirements;
(c) manual/physical job-skill requirements;
(d) digital job-skill requirements.

The charts below show the distributions of these scales at EU+ level.

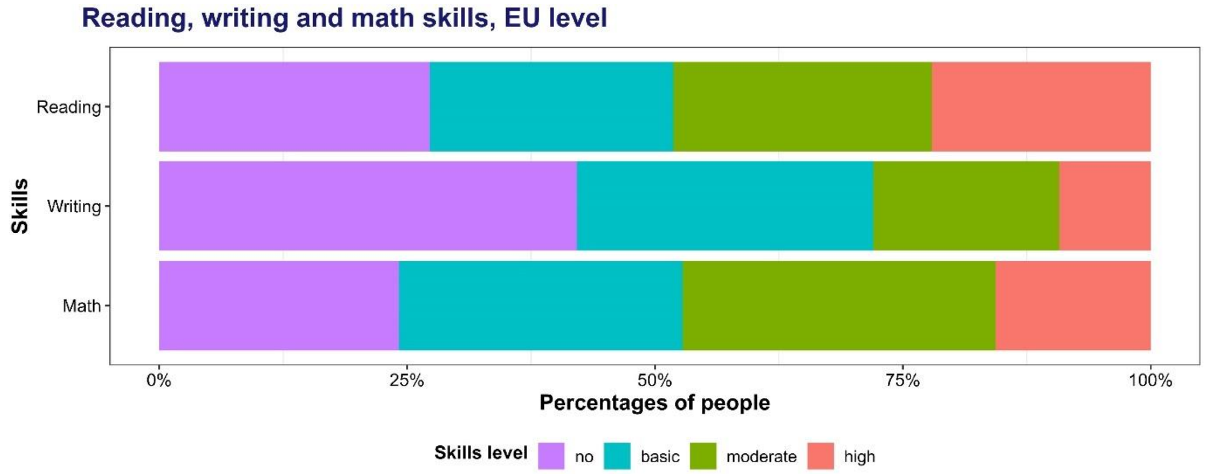
2.2.1. Foundation job-skill requirements

The variables which comprise foundation skill needs scale relate to reading, writing and maths skills (Figure 1). From their comparison, it emerges that the distributions of the reading and maths skill needs are similar, with around one quarter of employees employed in jobs requiring no skills and another quarter needing at most a basic skill level. The percentage of employees working in jobs that need a moderate skill level is higher for maths (31%) than for reading (26%) skills. For writing, the distribution of employees with a given level of skills is different, since the percentage of those in jobs that do not require any numeracy skill is much higher (42.7%).

Following analysis by Handel (2016) for the US and Matthes et al. (2014) for Germany, a scale summarising the foundation job-skill demands of EU+ adult workers is constructed based on the individual variables. Table 1 depicts the list of sub-components used to measure the foundation skills scale, together with the scores for internal consistency of the resulting scales, the Cronbach's alpha statistic. At a value of alpha = 0.75, it indicates a reasonably strong level of construct validity, although it is also clear that literacy and numeracy can also comprise two distinct subscales (since maths has an item-rest correlation lower than 0.50, indicating a less strong fit with the other items in the scale). The first principal component also accounts for 67% of the total variance, indicative of a strong dominant factor.

([6]) In this paper the terms 'job-skill requirements', 'skill needs' and 'skill demands' are used interchangeably, all describing the typical level of intensity of skills required by a worker to do his/her job.

Figure 1. **Foundation skills demand in EU+ labour market**



NB: Basic reading requirements correspond to jobs in which workers read texts, on paper or computer screens that are between one to four pages long; moderate reading is 5-24 pages long; high reading refers to texts that are at least 25 pages or longer. Writing requirements correspond to jobs in which workers write texts that are either at a basic level (one to four pages), moderate level (5-24 pages) or high level (more than 25 pages). Basic maths requirements imply that workers must perform simple calculations with numbers (adding, subtracting, multiplying or dividing) regularly as part of their job, whether on their own or with the help of a computer or calculator. Moderate mathematic requirements refer to jobs that require the use of simple algebra or mathematical formulas (for instance, calculating fractions or percentages or trying to find an unknown quantity). High maths refers to the use of any kind of more advanced mathematics, algebra or statistics, for instance calculus, regressions or simulation analysis.

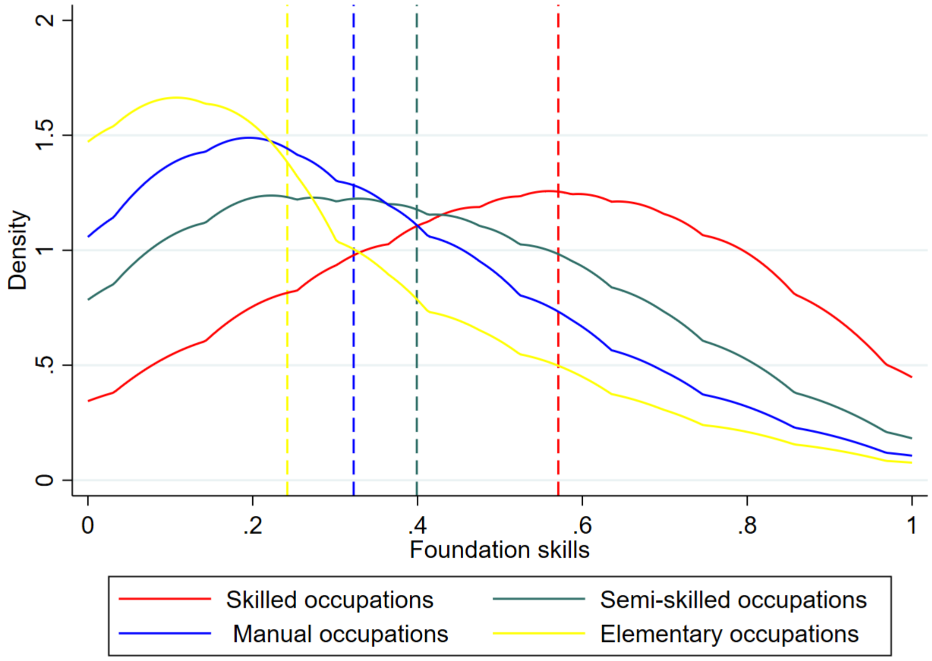
Source: Cedefop second European skills and jobs survey (ESJS2).

Table 1. **Validity of foundation skills demand scale**

	Item-rest correlation	PCA loading	Correlation with job education requirements	Correlation with individual education
Reading	0.66	0.61	0.41	0.35
Writing	0.64	0.61	0.37	0.32
Maths	0.46	0.50	0.29	0.25
Cronbach's α	0.75		0.44	0.38
Pct variance		0.67		

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 2. **Foundation skills demand by broad occupational group**



NB: The plot shows the variables k-density, a smoothed estimate of the probability density function. The x-axis of the graphs shows average values of the subscales in the respective skill domain that were normalised to a value ranging from 0 to 1, zero representing 'no skill content' and one 'very high skill content' of the respondent's job (in the respective task domain). As in Matthes et al. (2014), technically, this was achieved by recoding subscales to values from 0 to 4, adding them up and dividing them by the (theoretical) maximum item sum (e.g. 4 ∗ 3 = 12 for four subscales), resulting in the displayed scale values between 0 and 1. In order to make the figure easier to read, smoothed lines have been used instead of vertical bars per data point on the x-axis. Vertical lines indicate group means.

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 2 further examines the criterion validity of the construct: the extent to which the means of the foundation skill needs measure varies in reasonable direction across worker groups, notably occupation ([7]). The distributions corresponding to elementary and manual occupations (yellow and blue lines, respectively) are centred around lower mean values, while the distribution corresponding to skilled occupations (red line) and semi-skilled occupations (green line) are the ones centred around the highest mean values. It is also worth noting that the four distributions show different shapes. While manual and elementary occupations present higher density for low values, the opposite is true for skilled occupations, for which the highest density of the scale is reached around a value of 0.65. This means that low-skilled occupations present lower foundation job-skill requirements, in contrast to the higher ones of semi-skilled and skilled occupations.

We further confirm the criterion validity of the scale by the fact that its correlation with the ESJS2 measure of job educational requirements is higher compared to the personal

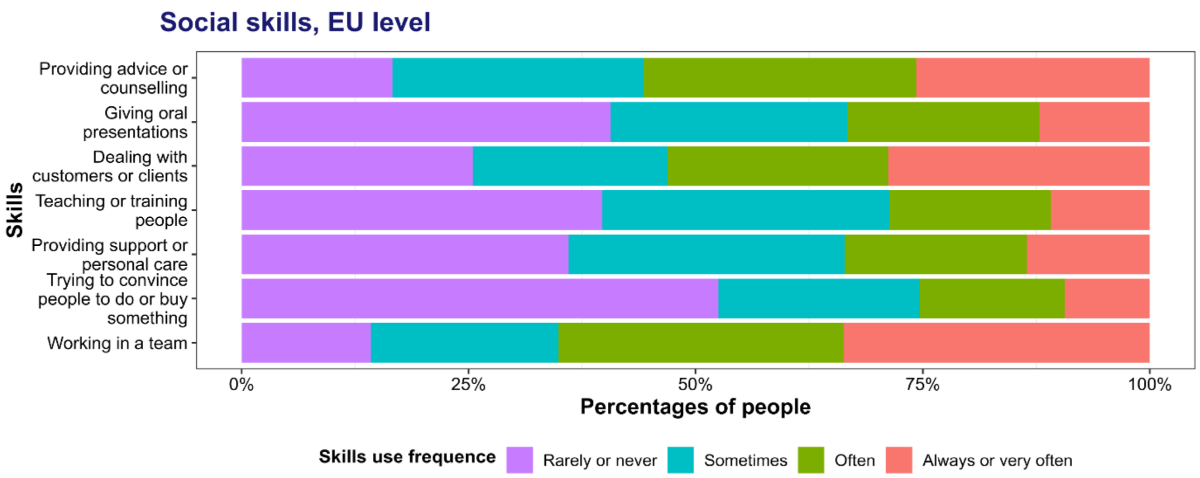
([7]) In this section we illustrate the analysis across four broad occupational groups, which capture the dispersion of skill needs across professions from high to low levels. Annex A1 further describes the results of the analysis done across nine detailed occupational groups, which confirms the robustness of the broader analysis.

educational attainment of individuals. This signifies that the construct provides valid insight into the level of skill demand in EU+ jobs, as opposed to be a proxy of worker skill supply.

2.2.2. Social job-skill requirements

The activities which pertain to ESJS2 social skill needs capture whether adult workers engage in the provision of advice and counselling, oral presentations, dealing with customers or clients, teaching or training, offering care services, selling or teamwork as part of their job (Figure 3). Providing advice, dealing with customers and working in a team are interpersonal tasks with the highest percentages of employees who perform them always or very often (between 25-33%). Trying to convince people to do or buy something is the least frequent activity, with the highest number of employees who perform it rarely or never (52.5%).

Figure 3. **Social skills demand in EU+ labour market**



Source: Cedefop second European skills and jobs survey (ESJS2).

With a Cronbach alpha value equal to 0.78, the social skill needs scale indicates reasonably high construct validity. This scale is also characterised by one strong dominant factor with eigenvalue that exceeds the value one, accounting for 44% of the total variance (Table 2). There is a higher correlation of the construct with the job education requirements variable, as opposed to individuals' highest level of educational attainment, although with small differences. This is likely to reflect greater diversity among interpersonal skills than other skills, their occupational specificity (e.g. selling, caring, teaching) and the fact that some (e.g. decision to engage in teamwork) might be ancillary job characteristics (masking attitudinal or motivational work aspects) rather than constituting specific job requirements (Handel, 2016).

As with the foundation skill needs scale, the distributions of social skill demands corresponding to elementary and manual occupations are centred around lower mean values, while the distributions corresponding to skilled and semi-skilled occupations are positioned more on the right part of the x axis (Figure 4).

Table 2. **Validity of social skills demand scale**

	Item-rest correlation	PCA loading	Correlation with job education requirements	Correlation with individual education
Advice and counselling	0.59	0.42	0.21	0.19
Oral presentations	0.57	0.42	0.17	0.14
Dealing with customers or clients	0.44	0.34	0.08	0.09
Teaching or training people	0.52	0.39	0.19	0.15
Providing support or personal care	0.51	0.38	0.11	0.09
Selling	0.52	0.39	0.05	0.06
Teamwork	0.37	0.29	0.15	0.13
Cronbach's α	0.78		0.21	0.18
Pct variance		0.44		

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 4. **Social skills demand by broad occupational group**

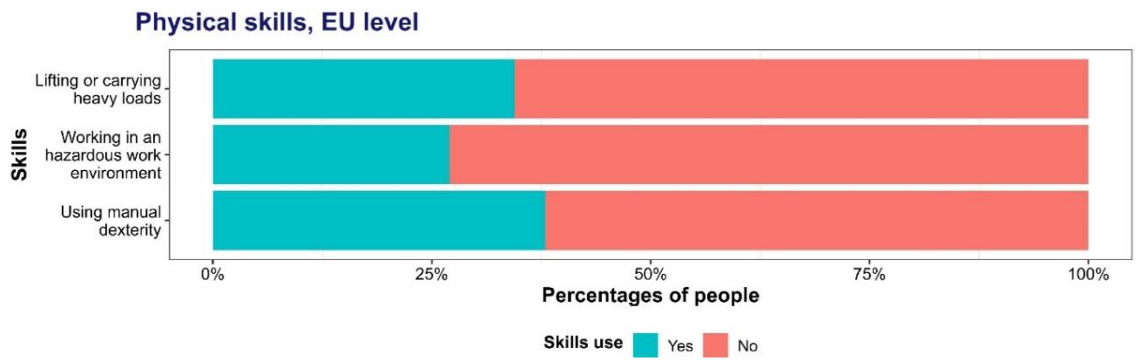
Source: Cedefop second European skills and jobs survey (ESJS2).

2.2.3. Physical job-skill requirements

The construction of the physical/manual skill needs scale combines three relevant ESJS2 binary variables (Figure 5) with information on whether EU+ workers have to carry or lift heavy objects or loads or people as part of their jobs without the help of a machine (35%), if they work in hazardous environments (e.g. with high heat or cold or chemical or dangerous parts) (27%) or if they have to use or move their hands or fingers to grasp, manipulate or assemble objects with precision at work (excluding using a mouse, typing or handwriting) (38%) ([8]).

With a Cronbach alpha value equal to 0.71, and higher (negative) correlation with job educational requirements than with personal education, there is evidence of strong construct and criterion validity of the physical skills scale (Table 3). One principal component with eigenvalue larger than one accounts for 63% of the total variance. Figure 6 further confirms that the survey responses on the physical skill demands items discriminate among the four broad occupational groups, with higher mean values and concentration on manual occupations, followed by elementary jobs, as would be expected. Higher skilled occupations, by contrast, demonstrate significantly lower reliance on physical/manual tasks.

Figure 5. **Physical skills demand in EU+ labour market**



Source: Cedefop second European skills and jobs survey (ESJS2).

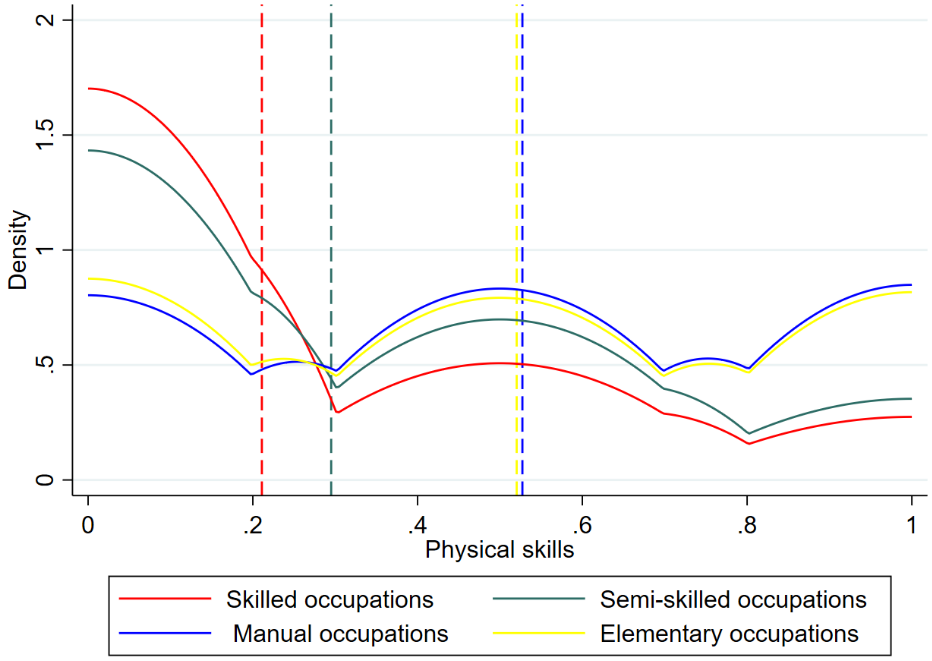
Table 3. **Validity of physical skills demand scale**

	Item-rest correlation	PCA loading	Correlation with job education requirements	Correlation with individual education
Heavy loads	0.50	0.59	-0.27	-0.22
Hazardous work environment	0.47	0.56	-0.19	-0.17
Manual dexterity	0.54	0.58	-0.20	-0.18
Cronbach's α	0.71		-0.27	-0.23
Pct variance		0.63		

Source: Cedefop second European skills and jobs survey (ESJS2).

([8]) The information on manual dexterity is only asked in the online component of the ESJS2, so the physical skills scale relies on the other two sub-components when the whole ESJS2 sample is used in empirical analyses, with somewhat lower validity (alpha = 0.60).

Figure 6. **Physical skills demand by broad occupational group**



Source: Cedefop second European skills and jobs survey (ESJS2).

2.2.4. Digital job-skill requirements

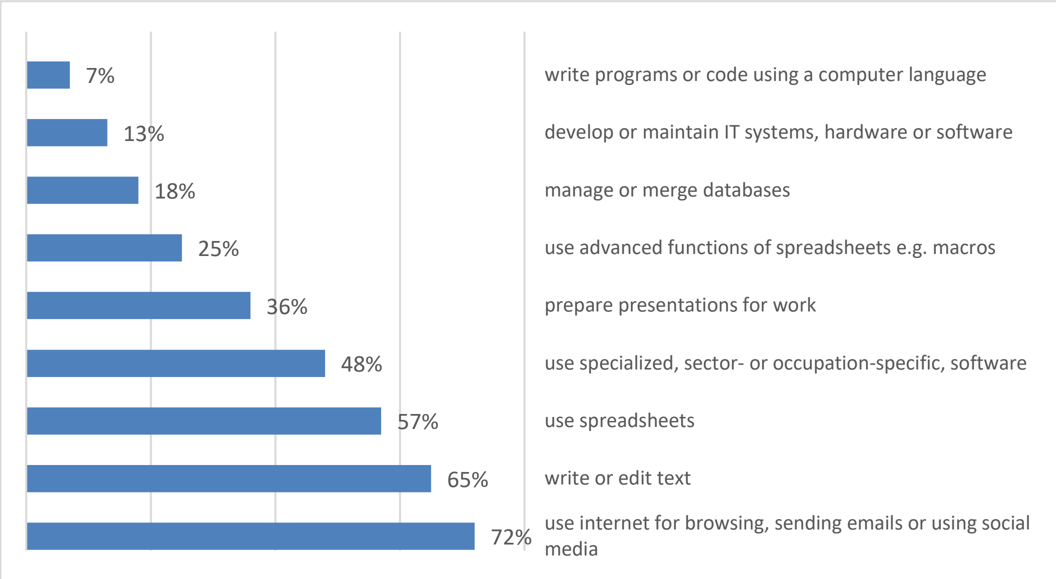
A digital skills intensity (DSI) index is derived to characterise jobs in terms of the intensity of use of digital technologies at work in the 29 European countries covered by the survey. The index is derived by summing up ESJS2 information on the digital intensity of EU+ jobs, proxied by the type of computer applications workers use as part of their work (e.g. web browsing to system maintenance) ([9]).

As shown in Cedefop (2022b), most EU+ workers (around 60-70%) require a basic or moderate digital skill level for their job (e.g. web browsing, emailing, word processing, use of spreadsheets), while about one in ten undertake advanced digital tasks at work (e.g. ICT development and maintenance, computer programming). 13% of EU+ adult workers do not use any digital device in their job, so they do not require any digital skills for work (Figure 7).

Analysis of the inter-item reliability of the digital skills index confirms that the digital activities load well on one factor, accounting for about 40% of the total variance, and a Cronbach's alpha analysis reveals that the resulting score is high ($\alpha = 0.83$) (Table 4). Analysis of the distribution of the construct across broad occupational groups further confirms its validity, given that more skilled occupations are also the more digitally intensive ones (Figure 7).

([9]) The DSI does not consider the type and frequency of use of different computerised machines, given that such information was only collected for the online component of the ESJS2 sample. Principal components analysis also reveals that the information on computerised machine use is distinct from that focused on computer activities. Therefore, the DSI is likely to underestimate the extent of digital skill demand in countries that make greater use of computer-based machines.

Figure 7. **Digital skills demand in EU+ labour market**



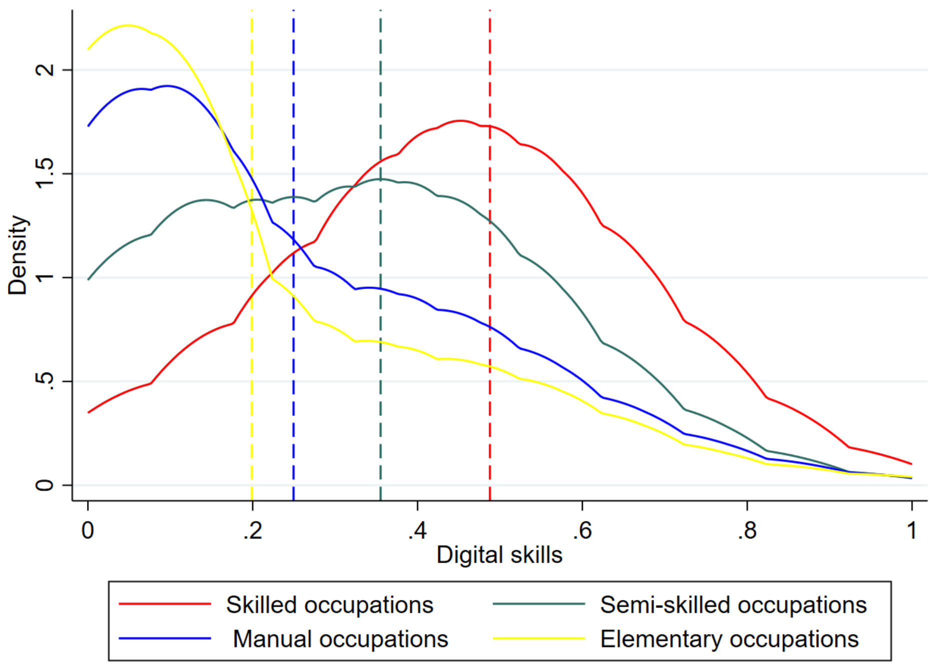
Source: Cedefop second European skills and jobs survey (ESJS2).

Table 4. **Validity of digital skill demands scale**

	Item-rest correlation	PCA loading	Correlation with job education requirements	Correlation with individual education
Use internet	0.49	0.30	0.38	0.33
Word processing	0.56	0.33	0.42	0.36
Spreadsheets	0.54	0.33	0.38	0.32
Specialised software	0.62	0.36	0.38	0.33
Presentations	0.58	0.35	0.38	0.22
Advanced spreadsheets	0.47	0.29	0.26	0.22
Database management	0.52	0.32	0.24	0.11
Programming	0.49	0.31	0.10	0.08
Programming using AI algorithms	0.42	0.27	0.03	0.02
ICT maintenance or development	0.46	0.29	0.10	0.08
Cronbach's α	0.83		0.45	0.38
Pct variance		0.39		

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 8. **Digital skill demands by broad occupational group.**



Source: Cedefop second European skills and jobs survey (ESJS2).

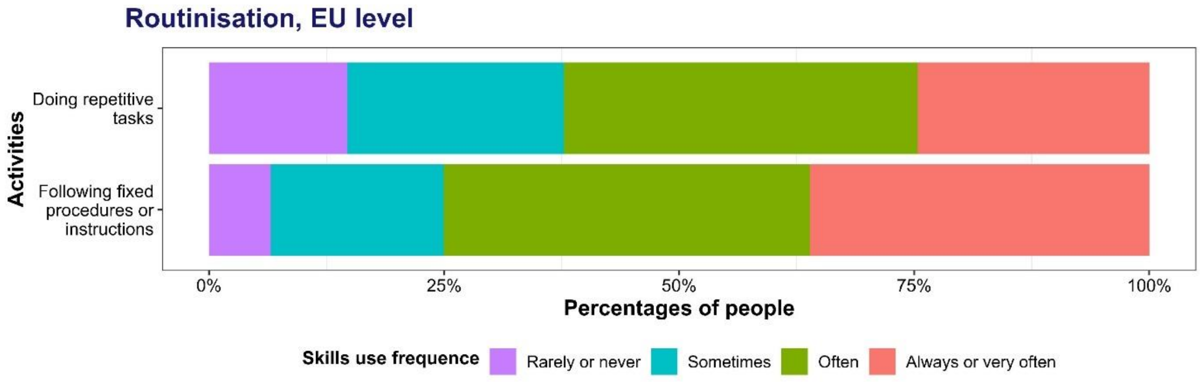
2.3. Profiling job complexity in EU+ labour markets

2.3.1. Work routinisation

The relevant ESJS2 information on work organisation is further utilised to construct two unique scales that proxy for the level of routinisation and complexity of an employee's job (Cedefop, 2022b).

Routinisation at work is defined by two types of activities which concern the execution of short, repetitive movements or tasks at work and the need to follow standardised instructions or procedures (Figure 9). Although the percentages of workers who sometimes or often perform either of these activities are similar for both variables, the percentage of workers who always or very often must follow fixed procedures or instructions is much higher than those who have to do repetitive tasks (36% instead of 25%).

Figure 9. **Work routinisation in EU+ labour market**



Source: Cedefop second European skills and jobs survey (ESJS2).

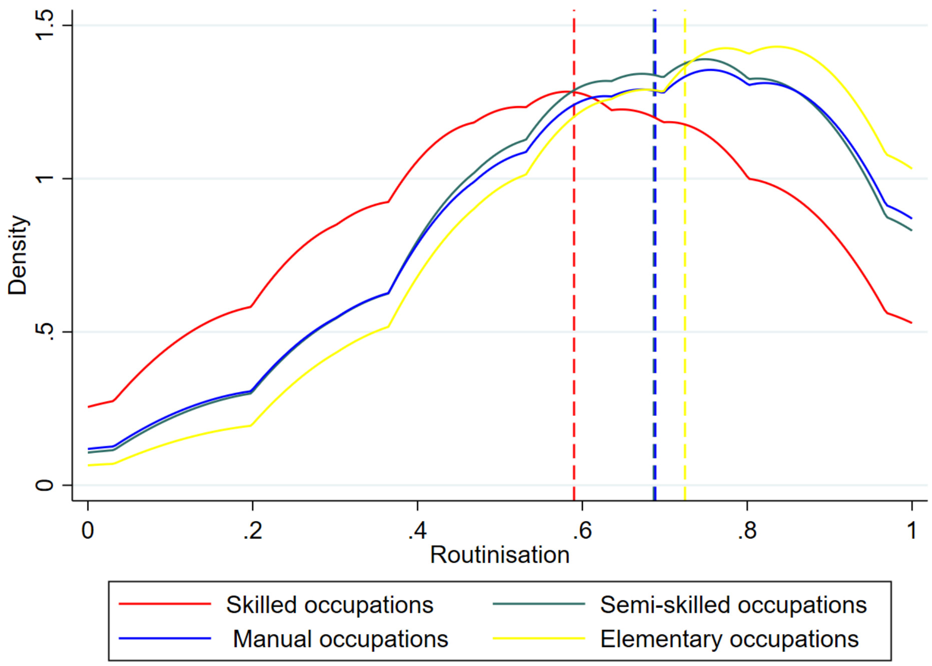
Table 5. **Validity of routinisation scale**

	PCA loading	Correlation with job education requirements	Correlation with individual education
Repetitive tasks	0.71	-0.26	-0.23
Fixed procedures	0.71	-0.14	-0.12
Cronbach's α	0.55	-0.25	-0.21
Pct variance		0.69	

Source: Cedefop second European skills and jobs survey (ESJS2).

Conversely to the skills scales described above, the highest mean values of the routinisation distributions are evident for elementary and manual occupations, and at their lowest for skilled occupations. However, a high routinisation density, comparable to that of manual occupations, is also observed for workers in semi-skilled occupations. The distributions exhibit a flatter left tail, indicating that, overall, a great share of workers often undertake some routine tasks in their jobs (Figure 10).

Figure 10. **Work routinisation by broad occupational group**



Source: Cedefop second European skills and jobs survey (ESJS2).

2.3.2. Job complexity

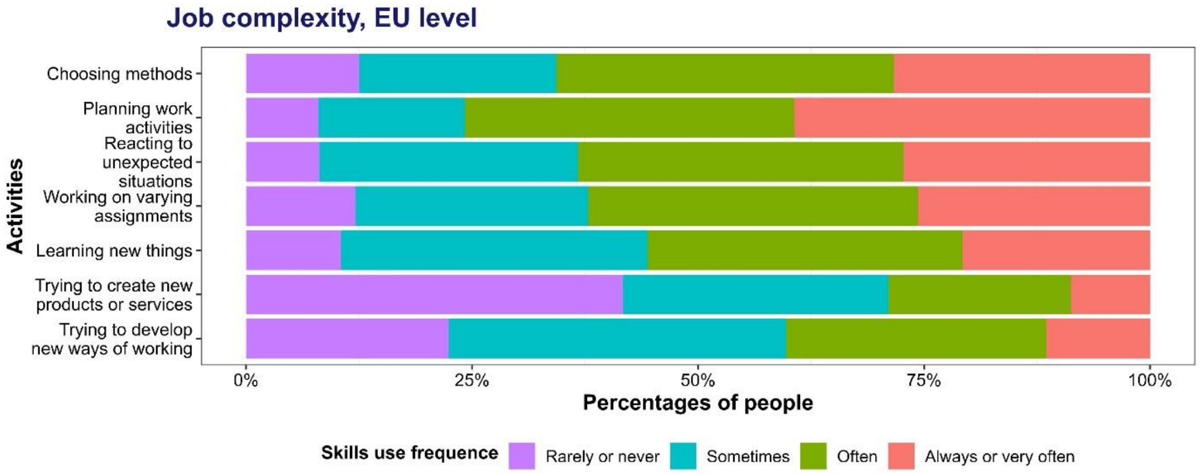
The complexity of a person's job can be measured by various aspects pertaining to the choice of methods or tools, the possibility to plan activities and work on different assignments, as well as the potential for learning and development, linked to the need for problem-solving or innovative capacity at work (Figure 11). Comparisons of the above elements indicates that the possibility to try and create new products or services is the least frequent job activity, since more than 40% of workers do this rarely or never. The possibility to plan one's own work activities is, instead, the most frequent activity, with 39% of workers doing it always or very often.

The Cronbach alpha value of 0.75 indicates that there is strong construct validity of the job complexity scale (Table 6). One dominant principal component also accounts for about 40% of the total variation. Overall, the job complexity scale exhibits a higher correlation with the educational requirements of jobs than with personal educational attainment.

The frequencies of the job complexity scale are normally distributed across all broad occupation categories (Figure 12). However, as with the routinisation scale, there is an almost complete overlap of the manual and semi-skilled occupational distributions. The mean value is higher for skilled occupations than for the other less-skilled categories, implying higher job complexity requirements for skilled workers. The scale clearly demarcates skill requirements at the high and low end of the occupational skills spectrum but fails to do so for medium-skilled occupational groups.

The derived skills and job complexity scales appear to be particularly useful for investigating possible differences in the job skill requirements across and within occupations.

Figure 11. **Job complexity in EU+ labour market**



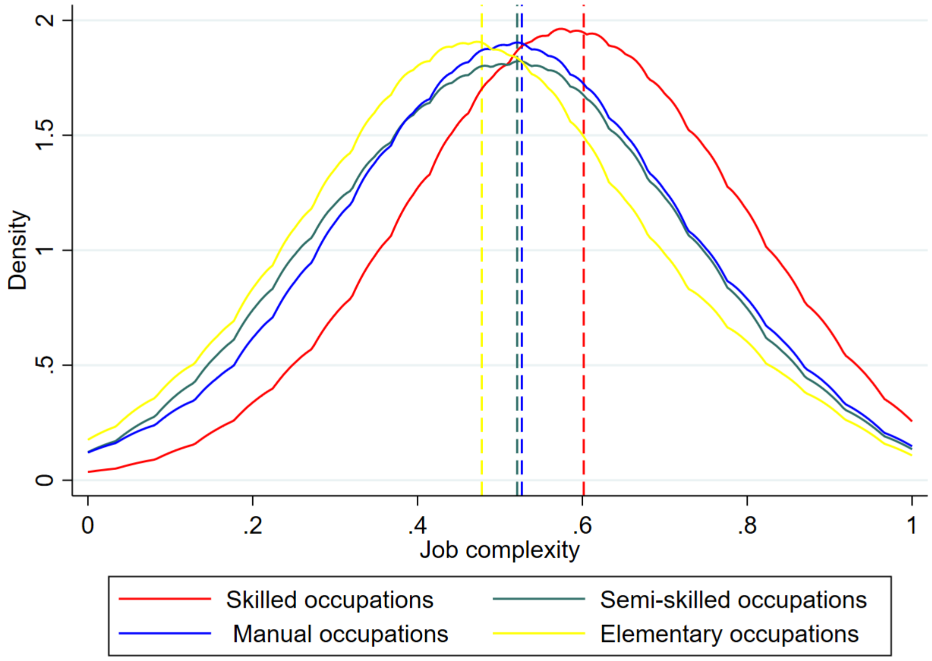
Source: Cedefop second European skills and jobs survey (ESJS2).

Table 6. **Validity of job complexity scale**

	Item-rest correlation	PCA loading	Correlation with job education requirements	Correlation with individual education
Choose methods	0.38	0.32	0.04	-0.01
Planning	0.44	0.36	0.18	0.13
Reacting to unexpected situations	0.44	0.36	0.11	0.08
Varying assignments	0.46	0.38	0.15	0.11
Learning new things	0.52	0.41	0.20	0.15
New products or services	0.47	0.39	0.19	0.14
New ways of working	0.53	0.42	0.18	0.14
Cronbach's α	0.75		0.25	0.17
Pct variance		0.40		

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 12. **Job complexity by broad occupational group**



Source: Cedefop second European skills and jobs survey (ESJS2).

2.4. Labour shortages in European labour markets

Given the detailed information on education and skill needs in different occupations and sectors, along with several other demographic and job quality indicators, ESJS2 data are a highly relevant source to examine in detail the determinants of labour and skill shortages in Europe.

Labour shortages observed in European job markets can arise because of numerous factors, such as unattractive working conditions, mobility constraints, high skill needs (e.g. cognitive, manual, social, digital) or changing skill needs induced by technological change or other mega-trends, insufficient skill supply, or a combination of these. In some cases, they can also be induced or sustained by the complexity and variability of skills required by firms for a given occupation. Underpinning the main reason(s) behind firms' recruitment difficulties is critical for making informed policy recommendations, such as whether it is possible to stimulate supply through education and training measures or by improving job design and worker retention.

In addition to defining labour and skill shortages, measuring them is an imperfect task and a multitude of approaches have been deployed in literature (Table A3 in Annex A3). In this study, we adopt an approach of using a detailed list of 4-digit occupations in shortage, as identified by the 2023 European Employment Services (EURES) report on labour shortages and surpluses of the European Labour Authority (ELA). The ELA list of occupational shortages is compiled by synthesising information provided by the EURES National Coordinating Offices (NCOs) in 27 EU Member States, three autonomous Belgian regions, plus Iceland, Liechtenstein, Norway and Switzerland. The source of such information mostly comes from administrative data of public employment services (PES), but also occupational forecasts and other combinations of sources.

To compile the list, each country/region is requested to identify shortage and surplus occupations based on various indicators, such as the ratio of registered job seekers to vacancies, employers' views, sourcing from abroad to fill vacancies, growth in employment faster than growth in education/training output, or if time required to fill vacancies is higher than average. For each identified shortage and surplus occupation, the countries also have to provide a measure defined in quantitative terms of the magnitude (low, medium, or high) and of the anticipated duration of the shortage or surplus (current, medium term or future) (McGrath, 2021).

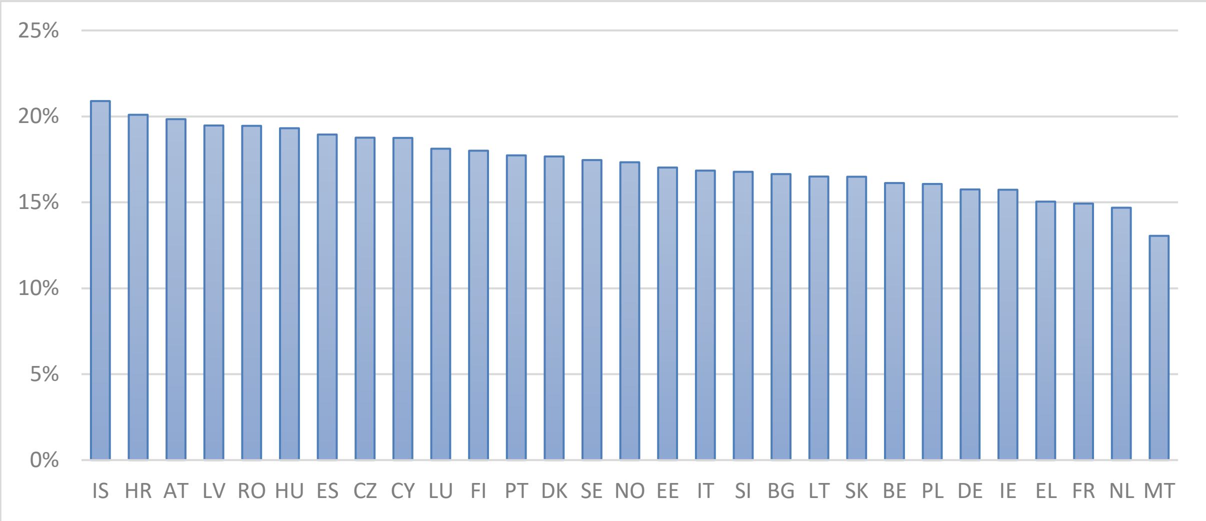
The main asset of this list clearly comes from its coverage at EU level, although this entails potential consistency issues among the information provided by the various countries. Additional examples of lists based on an indicator approach include the UK Shortage occupation list (SOL). This is compiled by the Migration Advisory Committee (MAC), using nine data-driven indicators of labour market conditions. The latter are derived from national representative datasets and combined with stakeholder evidence, also considering the possibility to fill those shortages with migrant workers. The Skills priority list (SPL) produced by Jobs and Skills Australia (JSA) and National Skills Commission (NSC) is based on extensive statistical analysis of the labour market, employer surveys and stakeholder engagement, and provides a current labour market rating for each occupation. The Canadian Occupational projection system (COPS) of Employment and Social Development Canada (ESDC) is a suite of models to identify labour market imbalances based on analysis of 20-30 indicators (including employment growth, unemployment rate, wage growth, employment insurance, job vacancies) and on consultation with external stakeholders and partners. Like the ELA list, these latter approaches are based on labour market indicators. However, since these lists are country specific, the collection of relevant information and indicators is facilitated at a deeper level with respect to the ELA EU list, reducing comparability and consistency issues.

The most recent list available at the time of writing this report refers to the latter half of 2021 and first half of 2022 period. From the ELA analysis, a total of 38 4-digit occupations is classified as 'most often': widespread shortages, of which 15 are also classified as shortages of 'high magnitude', the most severe.

To derive the main dependent variable for the analysis, we assembled a comprehensive list that compiles the 38 most often and high magnitude shortage occupations. We also added two elementary groups (cleaners and helpers in offices, hotels or domestic, corresponding to ISCO 3-digit category 911) that have also been identified in various sources as being prone to 'persistent' labour shortages (e.g. European Commission, 2023) (Table A4 in Annex A4). This final list of 38 4-digit (plus one 3-digit) occupations has been merged with data from Cedefop's ESJS2 at the 4-digit ISCO level, aiming to avoid any aggregation biases that could result from carrying out the analysis at broader ISCO levels.

About 17% of the EU employee population is employed in shortage occupations. Countries with a greater share of their workforce occupied in such occupations include Iceland, Croatia, Austria, Latvia, Romania and Hungary (Figure 13). The economies of Malta, Netherlands, France, and Greece, by contrast, have a relatively lower concentration of workers in shortage occupations.

Figure 13. **Share of paid adult workers in shortage occupations. EU+**



NB: The bars show the share of EU+ adult employees working in shortage occupations, as identified by ELA (2023).
Source: Cedefop second European skills and jobs survey (ESJS2)

The lists tend to confirm previous analyses (including those of Cedefop 2015, 2016) that have highlighted notable and persistent EU labour market tensions in the areas of ICT, health care, and STEM at both medium- and high-skill level. 55% of craft and related trades workers and 25% of plant and machine operators work in shortage occupations; this is also the case for about a fifth of professionals, service, and sales workers and one third of elementary workers. A higher share of those employed in shortage occupations is found in the following sectors: construction (42%), accommodation and food service activities (37%), human health and social work activities (31%), electricity, gas, steam, and air conditioning supply (23%), waste management (21%), transportation and storage (20%), manufacturing (19%) and ICT (18%) (Table 7).

Table 7. **Sectors with high shares of paid adult workers in shortage occupations, EU+**

NACE 1-digit	NACE 2-digit examples
Construction	• Specialised construction activities • Construction of buildings • Civil engineering
Accommodation and food service activities	• Accommodation • Food and beverage service activities
Human health and social work activities	• Residential care activities • Human health activities • Social work activities
Electricity, gas, steam, and air conditioning supply	• Electricity, gas, steam, and air conditioning supply

NACE 1-digit	NACE 2-digit examples
Water supply; sewerage, waste management	• Waste collection, treatment, and disposal activities; materials recovery
Transportation and storage	• Land transport
Manufacturing	• Repair and installation of machinery and equipment • Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles • Manufacture of fabricated metal products, except machinery and equipment • Manufacture of basic metals • Manufacture of furniture
ICT	• Computer programming, consultancy, and related activities • Information service activities

NB: Sectors with above EU+ average shares of workers in shortage occupations are displayed.
Source: Cedefop second European skills and jobs survey (ESJS2).

SECTION 3.
Empirical evidence: drivers of labour shortages

To investigate in depth the characteristics of occupational shortages, we use the relevant information from the Cedefop ESJS2 dataset to explore the possible reasons underlying the emergence of labour / skill shortages in occupations.

(a) High skill needs: skill shortages may arise because of high or dynamically changing skill demands in jobs, outpacing skill supply. Using a harmonised task-based approach, Cedefop's ESJS2 has collected robust measures of the intensity of demand for basic (literacy, numeracy), manual/physical, problem-solving, interpersonal, and digital skills in the jobs of EU+ adult workers. The ESJS also measures the extent to which the skills of EU+ workers need to be further developed so that they can proficiently perform their jobs, which may arise if technological or other organisational drivers increase the level of skill demand in jobs (skill gap). Evidence of significantly high(er) skill demands or skill gaps in shortage occupations relative to comparable jobs should support the claim that shortages are caused because of employer need to recruit people with greater knowledge and capabilities to carry out their job tasks proficiently.

(b) Skill mismatches: greater difficulties in finding available skill and talent in the external job market may result in the recruitment of individuals with lower skill level than required, hence underqualified workers. Conversely, when occupational shortages reflect recruitment difficulties or high labour turnover, or arise because of demand for a specific set of skills, they may simultaneously be characterised by high overqualification rates (individuals employed in jobs below their qualification level). Shortage occupations could therefore be associated with greater worker skill gaps / underskilling, particularly among newly hired workers, when they reflect genuine deficits of skill in the labour market. In contrast, they could be positively correlated with overqualification rates if they arise due to recruitment difficulties, other labour market frictions or bad working conditions. Cedefop's ESJS detects whether individuals' education level is more or less than that needed for their job, enabling the testing of the above hypotheses.

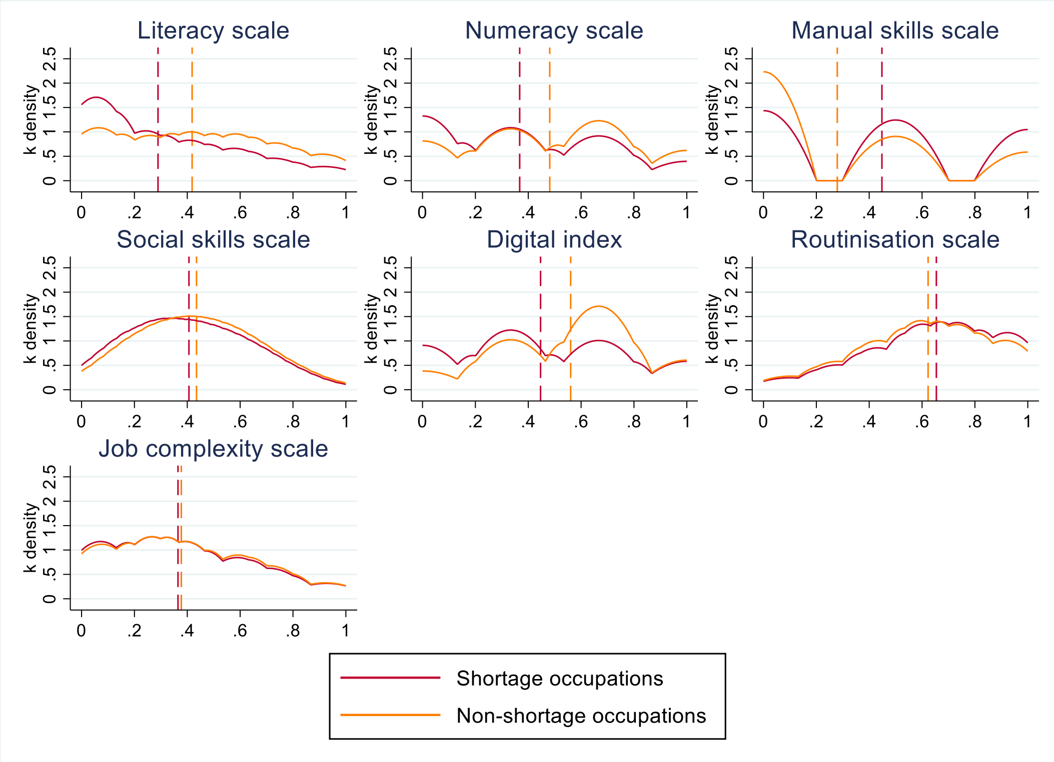
(c) Job quality: it is often argued that occupational shortages arise because of poor job offers, associated with non-competitive/low pay and bad working conditions. Although job quality is a multidimensional construct, Cedefop's ESJS2 contains several proxies of job quality in EU+ labour markets: job complexity, as measured by the extent to which EU+ workers have autonomy or leverage to plan in their jobs or have to learn and adapt to unexpected situations and perform varied tasks; routinisation, specifically whether EU+ workers have to do short, repetitive movements or tasks, or follow fixed, standardised procedures; worker subjective job satisfaction; and net monthly earnings. Other things being equal, occupational shortages associated with lower job complexity, higher routinisation, lower job satisfaction, and low wages are more likely to arise because of unattractive job offers or poor working conditions, as opposed to an inability to find people who are willing and skilled enough to work.

(d) Turnover and retention: related to poor job quality, occupations characterised by high retention difficulties and labour churning, as measured in the ESJS2 by workers' average years of job tenure, face a continuous need to replenish human capital. Shortages, in this case, are more likely to reflect poor HRM practices of firms and bad working conditions.

(e) Unexploited human capital: labour and skill shortages often arise because of poor career attractiveness in some sectors / occupations, or because recruitment and managerial practices fail to make the best use of available human resources in the labour market (Cedefop, 2015). It is well reported, for instance, that several ICT and STEM fields tend disproportionately to comprised males (Pouliakas and Livanos, 2012; European Commission, 2023). Demographic pressures (e.g. high replacement needs due to retirement, shifting generational preferences and attitudes) also breed shortages when a dwindling labour supply cannot meet rising personnel needs and (future) student cohorts also shrink in numbers.

(f) Labour mobility: labour / skill shortages are influenced by the location of advertised jobs and the extent to which worker geographic and labour mobility can ensure they are filled. Companies seeking labour in rural or more remote areas are more likely to face constraints in attracting and retaining labour. By contrast, agglomeration effects in larger cities may render the task of finding desired talent easier. ESJS2 information on rural-urban job location can be useful in considering the labour mobility / geographic aspect of shortages.

Figure 14. **Skill demand for shortage and non-shortage occupations, EU+**



NB: The plots show the variables k-density, that is a smoothed estimate of the probability density function. The x-axis of the graphs shows the values of the scales in the respective skill domain, rescaled to a value ranging from 0 to 1, with zero representing 'no skill content' and one 'very high skill content' of the respondent's job in the respective task domain.

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 14 shows to what extent skill demands vary between shortage and non-shortage occupations, indicated by red and orange lines, respectively. The distributions refer to the following scales of job-skill requirements and work complexity: literacy, numeracy, manual, social and digital skills, plus routinisation and job complexity. The dotted lines represent the average values of each scale. The differences between the mean values of the shortage and non-shortage occupations are statistically significant for all scales.

While the mean values of shortage occupations are lower than the mean values of non-shortage ones for most scales, the reverse is true for the manual and routinisation scales. This indicates that shortage occupations require a higher level of manual skills and routine tasks. Although for some scales the distributions for shortage and non-shortage occupations show very similar and sometimes overlapping shapes, shortage occupations overall present higher frequency of workers requiring more manual skills in their jobs, while the opposite can be observed for the literacy, numeracy, and digital skills scales.

Table 8 demonstrates the output of the empirical analysis focused on detecting the most significant characteristics of occupational skill shortages, using ESJS2 data. A probit multivariate regression model is deployed to detect the association between the cluster of variables described above, **X**, which constitute potential drivers of occupational shortages, and the probability that an individual *i* is employed in a shortage occupation, i.e.

$$P\,(s=1 \mid \boldsymbol{X}) = a + bX + u \quad (1)$$

where s=1 if an adult worker is employed in a 4-digit shortage occupation and s=0 otherwise; {a,b} are the model regression parameters to be estimated and u denotes the error term where it is assumed that $u \sim N(0,1)$.

Table 8 displays the regression coefficients and levels of statistical significance of the estimated statistical relationships. The analysis is first carried out for the whole sample of paid adult EU+ employees. To examine workers in shortage occupations who are as comparable as possible in terms of their 'skill' level to those in non-shortage ones, the analysis also implements the multivariate regression across broad occupational skill groups (i.e. skilled, semi-skilled, manual and elementary occupations) or even within the same cluster of 2-digit occupations when sample numerosity permits robust analysis (hence comparing 4-digit shortage and non-shortage occupations that are part of the same 'skills family').

When comparing shortage occupations with those that do not face marked hiring difficulties, it becomes evident that, on average, the former ones comprise jobs of lower average skill demand. Individuals working in shortage occupations are more likely to need lower literacy, numeracy, and digital skills. By contrast, such jobs depend more on physical/manual and (to some extent) interpersonal tasks. Even though their average skill needs are lower, employees in shortage occupations are expected to exercise greater discretion in organising and planning their work and in learning or adapting to unexpected situations or varying tasks. They also have significant scope to develop their skills further to be in tandem with those needed for better job performance. This could reflect the fact that there is a higher share of incumbent workers with insufficient skills in shortage occupations, or that the skill demand frontier is shifting faster in shortage than in non-shortage occupations, conditional on their existing skill supply.

The evidence therefore suggests that occupational shortages in the European economy are mostly an outcome of firms' expectations to find workers with high learning and adaptability skills. They also reflect some upskilling needs: a gap between the skills of workers and those needed to do their job as well as possible.

In addition to skill deficiencies, the demography of shortage occupations reveals that they mostly comprise male employees of a relatively younger/inexperienced age. Shortage occupations are less likely to depend on tertiary-education graduates. Geographic constraints, related to whether people live outside of middle-sized or large towns or cities, are not statistically relevant. There is little evidence to support the neoclassical argument that occupational shortages are a (temporary) disequilibrium that arises because of low pay that has not adjusted yet to the level required to attract job applicants. By contrast, shortage occupations are generally characterised by higher average wages relative to non-shortage ones.

While the above evidence already stresses the complexity of the underlying forces underpinning the wedge between labour demand and supply, it is confounded by the marked intra- and inter-occupational heterogeneity in both shortage and non-shortage 4-digit occupations. We therefore aim to restrict the analysis by comparing individuals belonging to occupations of 'similar' skill level. This is done both in broad terms and also by detecting differences among narrowly defined occupational clusters: as example, comparing science and engineering shortage professions only with comparable high-skilled or 2-digit occupations that have matched or surplus demand.

When focusing on broad skill groups, interesting differences between skilled and manual/low-skilled occupations emerge. The jobs of EU+ workers in semi-skilled and manual shortage occupations tend to be characterised by more complex / less routine tasks. Skill gaps among workers are mostly evident in skilled professions in shortage. Workers in skilled and semi-skilled shortage occupations are employed in jobs that need greater manual skills. Those in semi-skilled shortage occupations more often deploy social skills in their jobs. Semi-skilled shortage occupations, together with elementary ones, are more likely to have jobs that do not require digital skills.

Important demographic differences are further observed between the broad occupational groups. Skilled shortage occupations comprise mostly younger-aged, female workers and employ tertiary education graduates. Manual occupations in shortage overwhelmingly depend on male employees, indicative of a greater need to attract females towards what are typically male-dominated jobs.

Focusing only on narrow 4-digit occupational titles that are part of the same broader 2-digit family, an analysis done to reduce heterogeneity in the skill needs of occupations, it is further confirmed that the underlying determinants of shortages (and their combinations) may markedly differ between occupations ([10]). As shown in Figure 15 below as an example, the density of the job complexity scale for shortage occupations is higher than non-shortage occupations for ICT professionals and for legal, social, and cultural professionals. The reverse is true for science and engineering professionals and personal care workers, for whom occupational shortages are inversely related to job complexity.

The jobs of science and engineering professionals, health professionals, teaching professionals, personal care workers and metal, machinery, and related trades workers, among others, are also characterised by a greater prevalence of routine tasks (see Figure 16). Combined with a greater reliance on manual tasks, this would confirm, for instance, that shortages of health professionals / associates mostly reflect challenging working conditions as opposed to high skill needs.

Table 8. **Determinants of shortage occupations, EU+**

		All sample	Skilled	Semi-skilled	Manual	Elementary
Job skills requirements	**Literacy scale**	-0.0859***	-0.0533***	-0.0929***	0.00129	0.0609
		(-8.72)	(-6.78)	(-6.88)	(0.05)	(1.60)
	Numeracy scale	-0.0713***	-0.0868***	-0.0414	0.0196	-0.198***
		(-4.84)	(-9.95)	(-1.73)	(0.83)	(-7.87)

([10]) Results are available from the authors upon request. However, the robustness of such analysis is restricted by low numerosity at the 4-digit ISCO level for some shortage or non-shortage occupations.

		All sample	Skilled	Semi-skilled	Manual	Elementary
	Manual skills scale	0.113***	0.0837***	0.0888***	0.0300	-0.0768*
		(17.34)	(8.48)	(7.73)	(1.45)	(-2.42)
	Social skills scale	0.00222	0.0552*	0.0726**	0.145**	0.0296
		(0.10)	(2.57)	(3.09)	(2.87)	(0.28)
	Digital index					
	Non-user	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Low	-0.0795***	-0.0497	-0.0682***	0.0255	-0.123**
		(-6.32)	(-1.81)	(-3.92)	(0.77)	(-3.09)
	Medium	-0.132***	-0.0750**	-0.0848***	-0.0497	-0.190***
		(-13.53)	(-2.91)	(-5.32)	(-1.53)	(-6.44)
	High	-0.0787***	0.00248	-0.0609***	-0.0460	-0.140***
		(-6.18)	(0.08)	(-3.46)	(-0.95)	(-5.89)
Job quality	**Job complexity scale**	0.0426***	0.0103	0.0471**	0.000347	0.0272
		(3.81)	(0.82)	(3.22)	(0.01)	(0.39)
	Routinisation scale	-0.0180	-0.0247	0.00653	-0.0864*	0.0409
		(-1.50)	(-1.68)	(0.46)	(-2.49)	(1.28)
	Job satisfaction					
	Not satisfied	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Moderately satisfied	0.0172	-0.0189	-0.00845	0.0802*	0.0870*
		(1.47)	(-0.95)	(-1.03)	(2.09)	(2.28)
	Satisfied	0.0276*	-0.0154	0.000288	0.0997***	0.0731**
		(2.55)	(-0.74)	(0.03)	(3.89)	(3.07)
	Wages					
	Under lowest quartile	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Between lowest quartile and median	0.00654	-0.00967	0.0161**	0.0793***	0.00519
		(0.97)	(-1.53)	(2.59)	(4.83)	(0.10)

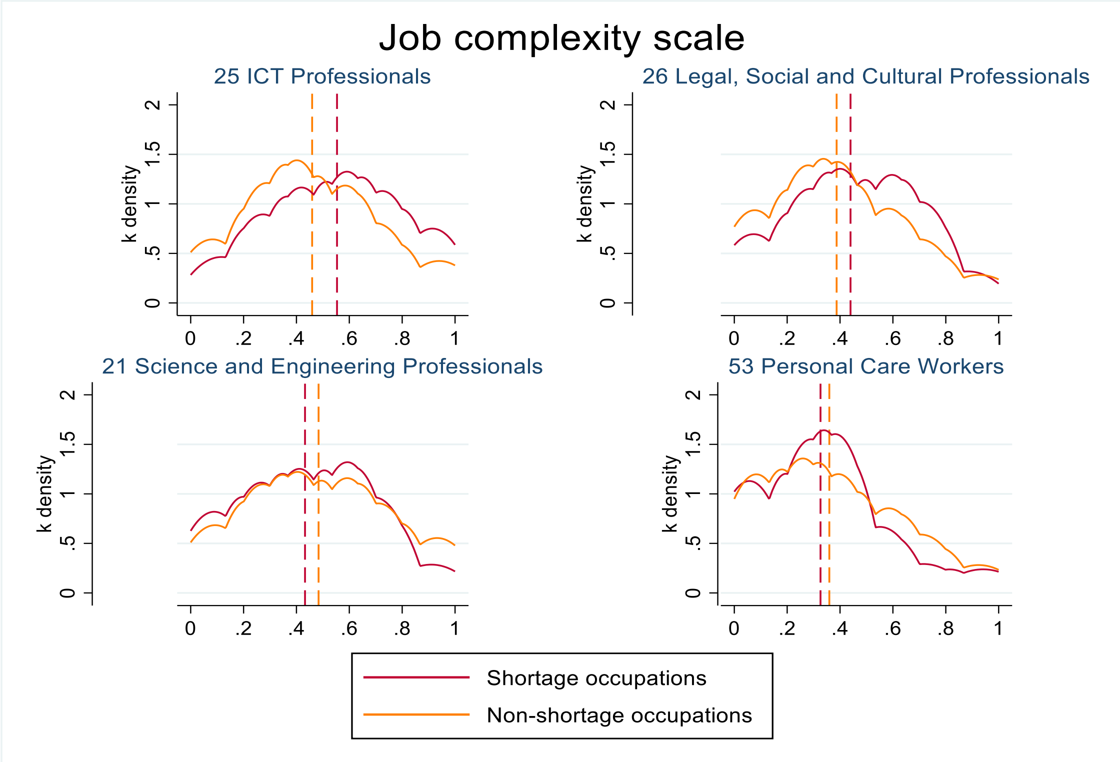
		All sample	Skilled	Semi-skilled	Manual	Elementary
	Between median and highest quartile	0.0266**	-0.00377	0.0193*	0.115***	-0.0816*
		(3.12)	(-0.53)	(2.41)	(7.54)	(-2.28)
	Above highest quartile	0.0490***	0.0103	0.0249	0.123***	0.00816
		(3.62)	(0.75)	(1.34)	(3.39)	(0.09)
Demography/ available human capital	**Age**					
	25-34	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	35-44	-0.0223*	-0.0229**	-0.0154	-0.0362	-0.0491
		(-2.48)	(-3.15)	(-1.43)	(-1.64)	(-1.11)
	45-54	-0.0103	-0.0207	-0.0171*	-0.00750	-0.0188
		(-1.07)	(-1.65)	(-2.42)	(-0.24)	(-0.59)
	55-64	-0.00182	-0.0198	-0.0100	0.0274	-0.0187
		(-0.16)	(-1.93)	(-0.59)	(0.78)	(-0.43)
	Male	0.0288**	-0.0327***	-0.00166	0.152***	-0.152***
		(2.88)	(-4.76)	(-0.25)	(5.30)	(-6.38)
	Education					
	Lower secondary education or below (ISCED 0-2)	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Upper secondary or post-secondary non-tertiary education (ISCED 3-4)	0.00192	0.0414***	-0.0188	-0.00813	0.0599**
		(0.18)	(3.40)	(-1.51)	(-0.50)	(2.88)
	Tertiary education (ISCED 5-8)	-0.0194*	0.0491***	-0.0194	-0.0713**	0.0174
		(-2.15)	(5.43)	(-1.49)	(-2.95)	(0.41)
Turnover	**Tenure**	-0.0000118	-0.000273	-0.000377	0.000669	0.00328
		(-0.02)	(-0.58)	(-0.51)	(0.24)	(1.87)
Skill mismatch	**Skill gap**					

		All sample	Skilled	Semi-skilled	Manual	Elementary
	Great extent	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Moderate extent	-0.0201*	-0.0179*	0.0115	-0.0302	0.0236
		(-2.23)	(-2.43)	(1.27)	(-0.76)	(0.87)
	Small extent	-0.0294***	-0.0391***	-0.00257	-0.0255	0.0211
		(-3.56)	(-4.00)	(-0.22)	(-0.91)	(0.87)
	Not at all	-0.0176	-0.0605***	0.000147	-0.0240	0.0652*
		(-1.79)	(-5.17)	(0.01)	(-0.73)	(2.09)
Mobility	**Area**					
	Rural area or village	0	0	0	0	0
		(.)	(.)	(.)	(.)	(.)
	Small or middle-sized town	-0.00276	0.00627	-0.00146	0.0142	-0.0229
		(-0.31)	(1.05)	(-0.10)	(1.52)	(-0.68)
	Large town or city	-0.0153	-0.00124	-0.00908	0.0321	-0.0438
		(-1.68)	(-0.24)	(-0.77)	(1.33)	(-1.17)
	Observations	41374	22586	11167	4829	2137

NB: The table displays the average marginal effects of a probit multivariate model where the dependent variable indicates if an adult worker is employed in a 4-digit shortage occupation. Other regressors not shown in the table include the required level of education for job, private sector, SME, permanent contract, hours of work, remote work, country dummies.

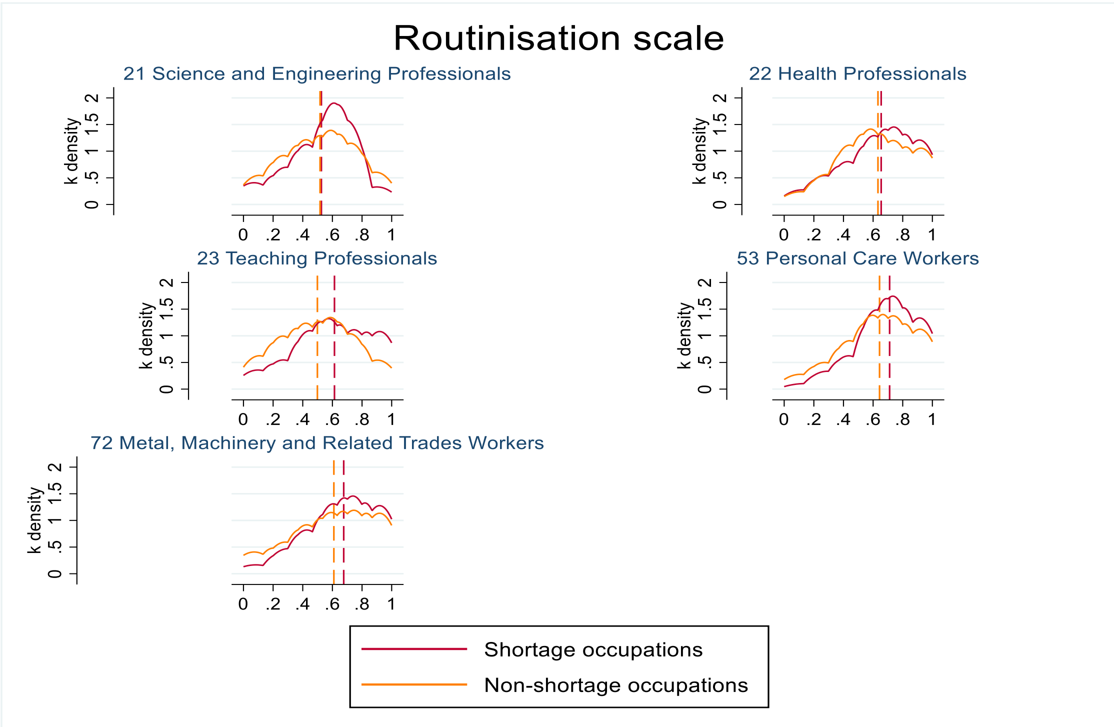
Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 15. **Job complexity for shortage and non-shortage occupations (ISCO 2-digit examples), EU+**



Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 16. **Routinisation for shortage and non-shortage occupations (ISCO 2-digit examples), EU+**



Source: Cedefop second European skills and jobs survey (ESJS2).

SECTION 4.
Within-occupation variation in skill needs and shortages

What the above evidence highlights is that there is no one-size fits all explanation and policy that may tackle the proliferation of labour shortages in European labour markets. Workers in shortage occupations are more likely to carry out relatively lower-skilled, manual tasks and some have jobs that entail the execution of routine work. ICT professionals seem to stand out in the high-skilled occupational category, in the sense that shortage jobs within this group require more autonomy and learning aptitude among job candidates. These are predominantly behavioural competences and traits that are more likely to be acquired on the job, and partly fostered via initial vocational education and training. Improvement in working conditions is instead more likely to be an effective recipe for mitigating health care shortages. Widening the talent pool in job vacancies for male dominated professions (e.g. personal service workers, electrical and electronic trades workers, drivers and mobile plant operators) to include female candidates, or attracting younger people in an ageing health care sector, may also serve to stem some of the shortages encountered in this occupational group.

The above analysis has focused on the inter-occupational differences in skill needs and job complexity between shortage and non-shortage jobs. However, this approach fails to consider the large variance in skill needs within the different occupations (Pouliakas and Russo, 2015; Russo, 2017).

Figure 17. **Distribution of social skill demands among '532 Personal care workers in health services' occupations, EU+**

Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 17 demonstrates the distribution in the demand for social skills among two prominent 'Personal care workers in health services' occupations that are usually in shortage, identified at 4-digit ISCO level: health care assistants and home-based personal care workers. This occupational group tends to be identified as one that has been in 'persistent' shortage over time and is likely to face accentuated future skills bottlenecks due to both high expansion and replacement demand (European Commission, 2023). The average social skill demand is slightly higher for health care assistants compared to home-based personal care workers, and the average level of social skills required in the respective ISCO 3-digit category falls between the two (inter- or between-occupation effect). Some jobs within both groups require a very low level of social skills, others a high proficiency level (intra- or within-occupation effect). Mitigating shortages in these groups may require policies that target both individuals who do not want to do the relatively low-skilled tasks requested by some organisations, as well as upskilling and reskilling those who aim to meet the high skill demands in jobs at the right of the distribution.

Table 9. **Summary statistics for 4-digit job titles within the '532 Personal care workers in health services', EU+**

	mean	sd	skewness	kurtosis	p25	p75	iqr
5321							
Literacy scale	.25898	.2564386	.7794994	2.934832	0	.3333333	.3333333
Numeracy scale	.2245064	.2724719	.9312005	2.902923	0	.3333333	.3333333

	mean	sd	skewness	kurtosis	p25	p75	iqr
Manual skills scale	.4588396	.3768798	.1362772	1.775215	0	.5	.5
Social skills scale	.4809962	.2097438	-.1015877	2.403233	.3333333	.6666667	.3333333
Digital index	.5052091	.2801683	-.0404045	2.418482	.3333333	.6666667	.3333333
Routinisation scale	.7114189	.2192695	-.5451102	2.935967	.6666667	.8333333	.1666666
Job complexity scale	.3260525	.2635519	.7216066	3.260576	.1666667	.5	.3333333
5322							
Literacy scale	.265818	.2754458	.8889657	2.911688	0	.5	.5
Numeracy scale	.2643633	.2985702	.7537993	2.439981	0	.3333333	.3333333
Manual skills scale	.4458967	.3378945	.1335014	2.179591	0	.5	.5
Social skills scale	.4593996	.2004308	.1107455	2.862834	.3333333	.5714285	.2380952
Digital index	.4139284	.279369	.1910701	2.415694	.3333333	.6666667	.3333333
Routinisation scale	.6759126	.247364	-.5385318	2.794598	.5	.8333333	.3333333
Job complexity scale	.3627015	.2774338	.4864851	2.472896	.1666667	.5	.3333333
5329							
Literacy scale	.2542307	.2161175	.7812311	3.642635	0	.3333333	.3333333
Numeracy scale	.2382984	.2778367	.5683751	1.714687	0	.3333333	.3333333
Manual skills scale	.5003539	.473692	-.0014044	1.14898	0	1	1
Social skills scale	.4741764	.1822057	-.1097467	2.474845	.3333333	.6190476	.2857143
Digital index	.4780124	.1964729	.0566801	2.508574	.3333333	.6666667	.3333333
Routinisation scale	.7493901	.252856	-.2760217	1.557545	.5	1	.5
Job complexity scale	.3771539	.26349	.1874342	1.9866	.1666667	.6666666	.5
Total							
Literacy scale	.263622	.2685003	.8686811	2.960906	0	.3333333	.3333333
Numeracy scale	.2530442	.2915276	.7979233	2.537452	0	.3333333	.3333333

	mean	sd	skewness	kurtosis	p25	p75	iqr
Manual skills scale	.4512246	.3537648	.1406423	2.000539	0	.5	.5
Social skills scale	.4655197	.202296	.0485801	2.709281	.3333333	.6190476	.2857143
Digital index	.4400082	.2797859	.1198126	2.40442	.3333333	.6666667	.3333333
Routinisation scale	.6877395	.2411466	-.5424886	2.826678	.5	.8333333	.3333333
Job complexity scale	.3537121	.2736523	.5360204	2.623668	.1666667	.5	.3333333
Observations	1107						

Source: Cedefop second European skills and jobs survey (ESJS2).

As a further example, Table 9 shows the summary statistics for all scales related to job skill requirements and job characteristics for the ISCO 4-digit job titles within the category ‘Personal care workers in health services’. In addition to different mean values of social skills required, it emerges that the three job titles also differ with respect to numeracy and digital skills and to the routinisation and job complexity needed at work. These titles also exhibit high variability for manual skills.

A one-way analysis of variance (ANOVA) ([11]) helps to assess whether the differences in the scales across, but also within, occupations are statistically significant. This allows us to determine if there is a statistically significant difference between the means of independent, unrelated, groups, based on the ratio of two components of the total variation (Table 10) ([12]).

Table 10. **ANOVA analysis: between and within variation in job-skill requirements**

	SS	df	MS	F	Bartlett’s equal - variances test
10(a) ISCO 1-digit					
Foundation skill demands					
ISCO 1-digit					
Between groups	665.743	8	83.2178	1283.91***	
Within groups	2937.4551	45320	.0648		
					chi2(8) = 909.6110***
Social skill demands					

([11]) Detailed explanations about the ANOVA are provided in the Annex A2. Results of the ANOVA at ISCO 4-digit occupations level are available from the authors upon request (the analysis cannot be performed for category 6. Skilled agricultural, forestry and fishery workers, given its low sample size).

	SS	df	MS	F	Bartlett's equal - variances test
Between groups	216.0266	8	27.0033	571.26***	
Within groups	2125.7163	44970	.0472		
					chi2(8) = 1.2e+03***
Digital skill demands					
Between groups	5041.1837	8	630.1479	904.1***	
Within groups	31587.6072	45320	.6969		
					chi2(8) = 5.3e+03***
Physical skill demands					
Between groups	847.7914	8	105.9739	819.03***	
Within groups	5856.4114	45262	.1293		
					chi2(8) = 4.3e+03***
Routinisation					
Between groups	186.8719	8	23.3589	358.76***	
Within groups	2926.4882	44947	.0651		
					chi2(8) = 887.3842***
Job complexity					
Between groups	179.328	8	22.416	282.99***	
Within groups	3577.3868	45163	.0792		
					chi2(8) = 1.4e+03***
10(b) ISCO 4-digit ([13]) – Foundation skill demands only					
Managers					
Between groups	16.5098	18	.9172	14.62***	61.8257***
Within groups	297.4345	4741	.0627		
Professionals					
Between groups	104.2193	46	2.2656	36.35***	406.967***
Within groups	707.4267	11351	.0623		
Technicians and associate professionals					

([13]) Only 4-digit occupations with more than 90 observations are considered.

	SS	df	MS	F	Bartlett's equal - variances test
Between groups	16.2138	17	.9537	15.37***	123.9531***
Within groups	278.2565	4590	.0606		
Clerical support workers					
Between groups	28.4039	16	1.7752	29.91***	58.6418***
Within groups	340.7524	5741	.0593		
Service and sales workers					
Between groups	18.8055	15	1.2537	21.87***	128.0157***
Within groups	296.6034	5174	0.0573		
Craft and related trades					
Between groups	3.8933	8	.4866	8.09***	23.3998***
Within groups	100.147	1665	.0601		
Plant and machine operators and assemblers					
Between groups	1.4342	5	.2868	6.94***	28.288***
Within groups	49.0623	1187	.0413		
Elementary occupations					
Between groups	14.1247	8	1.7655	38.10***	193.1952***
Within groups	88.2251	1904	.0463		

Source: Cedefop second European skills and jobs survey (ESJS2).

The ANOVA analysis shows that the differences in the mean values of all six ESJS2 scales are statistically significant for all ISCO 1-digit categories, with only few exceptions ([14]). The ANOVA can also be performed at a more disaggregated level of ISCO 4-digit occupations, to assess whether there is significant variation in skill needs also within each ISCO 1-digit category. Comparing the variation across ISCO 4-digit occupations to the variation within ISCO 4-digit occupations, for each ISCO 1-digit category, it emerges that the between variation is large compared to the within variation. This shows that there is evidence of a group difference

([14]) For instance, the categories 8. Plant and machine operators and assemblers and 9. Elementary occupations are not significantly different between them in terms of mean values of the cognitive and social skills scales. The categories 1. Managers and 2. Professionals are also not significantly different in terms of mean values of the routinisation and job complexity scales.

in the mean values of the scales across the narrower 4-digit ISCO occupations that are included in a broader ISCO 1-digit grouping ([15]).

The ANOVA analysis confirms that while there are significant differences in skill needs and job complexity between ISCO 1-digit broad occupational groups, focusing only on such variation (i.e. inter-occupational composition effects) is likely to underestimate the marked dispersion in job-skill requirements/complexity across different minor (4-digit) occupations (intra-occupation effect). The latter has been shown in relevant literature to explain most of the variation in automation and labour market outcomes (Freeman et al., 2020). Given that such heterogeneity of skill demands within broad occupations but also within narrow occupations is likely to reflect firms' different recruitment and job design practices, it is important to take this into account when explaining their difficulties in recruiting labour at different skill levels.

([15]) The only exception is the category 8. Plant and machine operators, and assemblers for both the routinisation and job complexity scales. This means that the variation between ISCO 4-digit occupations which belong to this broader ISCO category is not significantly different from zero.

SECTION 5.
Conclusions

In this paper we have used the information on literacy, numeracy, digital and interpersonal skills collected through Cedefop's ESJS2 task-based module, to measure the level of skills required in European jobs. Based on these ESJS2 variables, relevant composite scales of job-skill requirements (foundation skills, social skills, manual skills, digital skills) and of routinisation and job complexity have been constructed.

After an assessment of the scales' construct and criterion validity, we perform an empirical investigation of the relationship between jobs' skill needs and the occurrence of occupational labour shortages. We also explore other possible drivers of firms' recruitment challenges, such as labour market mobility, workers' skill deficiency, and unattractive working conditions.

From the regression analysis it emerges that workers in shortage occupations are more likely to carry out relatively lower-skilled, manual tasks. For some, their jobs also entail the execution of highly routine work. ICT professionals seem to stand out in the high-skilled occupational category, in the sense that shortage jobs within this group require more autonomy and learning aptitude among job candidates. These are predominantly behavioural competences and traits that are more likely to be acquired on the job, and partly fostered via initial vocational education and training.

While greater upskilling investments may be needed to tackle shortages in some occupations, for others (e.g. health care) improvement in working conditions is more likely to be an effective recipe. Widening the talent pool in job vacancies to include candidates of alternative gender or age may also serve to stem some of the shortages encountered in some gender-dominated occupational groups.

Using an ANOVA analysis, we further show that there is marked variability in the skills required within both broad and narrow occupational groups. The differences in the mean values of the job-skill requirements/complexity scales are statistically significant, not only between ISCO 1-digit broad occupational groups, but also between narrow ISCO 4-digit occupations within each category. This highlights that job-skill requirements/complexity are also different across the specific occupations within a given broad ISCO category. It implies that any shortage analysis should be, at the very minimum, performed at 4-digit ISCO level.

Such skills variability is likely to reflect the relatively idiosyncratic human resource practices that firms deploy for attracting and using skills in their workplaces. To design effective skills policies, it is critical to acknowledge that a one-size-fits all approach, such as one focused only on upskilling or reskilling investments, is likely to fall short of effectively mitigating different types of labour and skill shortages in European labour markets.

References

[URLs accessed 16.1.2024]

Acemoğlu, D., & Pischke, J. (1999). Beyond Becker: training in imperfect labour markets. *The Economic Journal*, 109(453), 112–142. https://doi.org/10.1111/1468-0297.00405

Almeida, R., Behrman, J. R., & Robalino, D. A. (2012). *The right skills for the job? Rethinking training policies for workers.* World Bank Publications. https://ideas.repec.org/b/wbk/wbpubs/13075.html

Arrow, K. J., & Capron, W. M. (1959). Dynamic shortages and price rises: The Engineer-Scientist Case. *The Quarterly Journal of Economics*, 73(2), 292. https://doi.org/10.2307/1883726

Australian Government National Skills Commission (2022). *Skill shortage list*. https://www.nationalskillscommission.gov.au/topics/skills-priority-list

Barnow, B. S., Trutko, J., & Piatak, J. (2013). *Occupational Labor Shortages: Concepts, causes, consequences, and cures*. https://doi.org/10.17848/9780880994132

Bartel, A. P., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-Level comparisons of product innovation, process improvement, and worker skills. *The Quarterly Journal of Economics*, 122(4), 1721–1758. https://doi.org/10.1162/qjec.2007.122.4.1721

Becker G (1967). *Human capital and the personal distribution of income: an analytical approach.* In Human Capital. 2nd edition. University of Michigan, Institute of Public Administration, Ann Arbor, MI; 1967.

Bell, D., & Blanchflower, D. G. (2019). The well-being of the overemployed and the underemployed and the rise in depression in the UK. *Journal of Economic Behavior and Organization*, 161, 180–196. https://doi.org/10.1016/j.jebo.2019.03.018

Bennett, J., & McGuinness, S. (2009). Assessing the impact of skill shortages on the productivity performance of high-tech firms in Northern Ireland. *Applied Economics*, 41(6), 727–737. https://doi.org/10.1080/00036840601007450

Bisello, M., Fana, M., Fernández-Macías, E., & Pérez, S. T. (2021). *A comprehensive European database of tasks indices for socio-economic research*. JRC Working Papers Series on Labour, Education and Technology, 2021/04. https://www.eurofound.europa.eu/en/publications/eurofound-paper/2021/comprehensive-european-database-tasks-indices-socio-economic

Boswell, C., Stiller, S., & Straubhaar, T. (2004). *Forecasting labour and skills shortages: how can projections better inform labour migration policies?* (pp. 21-38). EC, DG Employment and Social Affairs.

Brunello, G., & Wruuck, P. (2021). Skill shortages and skill mismatch: a review of the literature. *Journal of Economic Surveys*, 35(4), 1145–1167. https://doi.org/10.1111/joes.12424

Cappelli, P. H. (2015). Skill gaps, skill shortages, and skill mismatches: evidence and arguments for the United States. *ILR Review,* 68(2), 251-290. https://www.nber.org/papers/w20382

Cedefop (2010). *The skill matching challenge.* Publications Office of the European Union. https://data.europa.eu/doi/10.2801/23851

Cedefop, (2015a). *Skill shortages and gaps in European enterprises: striking a balance between vocational education and training and the labour market.* Publications Office of the European Union. https://data.europa.eu/doi/10.2801/042499

Cedefop, (2015b). *Skills, qualifications and jobs in the EU: the making of a perfect match?: evidence from Cedefop's European skills and jobs survey*. Publications Office of the European Union. https://data.europa.eu/doi/10.2801/606129

Cedefop (2016). *Skill shortage and surplus occupations in Europe: Cedefop insights into which occupations are in high demand and why.* Publications Office of the European Union. https://data.europa.eu/doi/10.2801/05116

Cedefop, (2018). Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey. Publications Office of the European Union. https://data.europa.eu/doi/10.2801/645011

Cedefop, (2019). *Online job vacancies and skills analysis: a Cedefop pan-European approach.* Publications Office of the European Union. https://data.europa.eu/doi/10.2801/097022

Cedefop (2022a). *Challenging digital myths: first findings from Cedefop's second European skills and jobs survey.* Publications Office of the European Union. http://data.europa.eu/doi/10.2801/818285

Cedefop (2022b). *Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey.* Publications Office of the European Union. http://data.europa.eu/doi/10.2801/253954

Cedefop (2023). *Skills in transition: the way to 2035.* Publications Office of the European Union. http://data.europa.eu/doi/10.2801/438491

Cedefop; European Commission; ETF et al. (2021). *Perspectives on policy and practice: tapping into the potential of big data for skills policy.* Publications Office of the European Union. https://data.europa.eu/doi/10.2801/25160

Dawson, N.; Rizoiu, M. A.; Johnston, B.; & Williams, M. A. (2020). Predicting skill shortages in labor markets: A machine learning approach. In *2020 IEEE International Conference on Big Data (Big Data),* 3052-3061. https://ieeexplore.ieee.org/document/9377773

Deming, D. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4), 1593–1640. https://doi.org/10.1093/qje/qjx022

Deming, D., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1), S337–S369. https://doi.org/10.1086/694106

European Commission (2014a). *Mapping and analysing bottlenecks in EU labour markets: overview report: final.* Publications Office of the European Union.

European Commission (2014b). *European vacancy and recruitment report 2014*. Publications Office of the European Union.

European Commission (2022), *Labour market and wage developments in Europe: annual review 2022*. Publications Office of the European Union. https://data.europa.eu/doi/10.2767/128906

European Commission (2023). Employment and social developments in Europe (ESDE) 2023. Publications Office of the European Union. https://data.europa.eu/doi/10.2767/089698

European Labour Authority (2023). EURES Report on labour shortages and surpluses 2022. Publications Office of the European Union. https://data.europa.eu/doi/10.2883/50704

Felstead, A., Gallie, D., Green, F., & Zhou, Y. (2007). *Skills at work 1986 to 2006*. ESRC Center on Skills, Knowledge, and Organisational Performance. https://orca.cardiff.ac.uk/id/eprint/68042/

Fernández-Macías, E., & Bisello, M. (2021). A comprehensive taxonomy of tasks for assessing the impact of new technologies on work. *Social Indicators Research*, 159(2), 821–841. https://doi.org/10.1007/s11205-021-02768-7

Fernández-Macías, E., Bisello, M., Hurley, J. (2016a). *What do Europeans do at work?: a task-based analysis : European jobs monitor 2016.* Eurofound. Publications Office. https://data.europa.eu/doi/10.2806/12545

Fernández-Macías, E., Bisello, M., Sarkar, S., and Torrejón, S. (2016b). *Methodology of the construction of task indices for the European Jobs Monitor*. Eurofound.

Flisi, S., & Santangelo, G. (2022). Occupations in the European labour market during the COVID-19 pandemic. *Intereconomics*, 57(2), 120–126. https://doi.org/10.1007/s10272-022-1040-y

Forth, J., & Mason, G. (2006). *Do ICT skill shortages hamper firms' performance?: evidence from UK benchmarking surveys*. National Institute of Economic and Social Research.

Freeman, R. B., Ganguli, I., & Handel, M. (2020). Within-occupation changes dominate changes in what workers do: a shift-share decomposition, 2005–2015. *AEA Papers and Proceedings*, 110, 394–399. https://doi.org/10.1257/pandp.20201005

Green, F. (2012). Employee involvement, technology and evolution in job skills: a task-based analysis. *ILR Review*, 65(1), 36-67. https://doi.org/10.1177/001979391206500103

Green, F., Machin, S., & Wilkinson, D. S. (1998). The meaning and determinants of skills shortages. *Oxford Bulletin of Economics and Statistics*, 60(2), 165–187. https://doi.org/10.1111/1468-0084.00093

Green, F., Felstead, A., Gallie, D., & Henseke, G. (2016). Skills and work organisation in Britain: a quarter century of change. *Journal for Labour Market Research*, 49(2), 121–132. https://doi.org/10.1007/s12651-016-0197-x

Handel, M. J. (2003). Skills mismatch in the labor market. *Annual Review of Sociology,* 29(1), 135-165. https://doi.org/10.1146/annurev.soc.29.010202.100030

Handel, M. J. (2016). What do people do at work? A profile of U.S. jobs from the Survey of Workplace Skills, Technology, and Management Practices (STAMP). *Journal for Labour Market Research,* 49(2):177-197. https://doi.org/10.1007/s12651-016-0213-1

Handel, M. J. (2020). *Job skill requirements: levels and trends.* WotF Working Paper 02 2020

Haskel, J., & Martin, C. (1993). Do skill shortages reduce productivity? Theory and evidence from the United Kingdom. *The Economic Journal*, 103(417), 386-394. https://doi.org/10.2307/2234777

Healy, J., Mavromaras, K., & Sloane, P. J. (2015). Adjusting to skill shortages in Australian SMEs. *Applied Economics,* 47(24), 2470–2487. https://doi.org/10.1080/00036846.2015.1008764

Lazear, E. P. (2009). Firm-specific human capital: a skill-weights approach. *Journal of Political Economy*, 117(5), 914–940. https://doi.org/10.1086/648671

Lazear, E. P., & Spletzer, J. R. (2012). Hiring, churn, and the business cycle. The American Economic Review, 102(3), 575–579. https://doi.org/10.1257/aer.102.3.575

Livanos, I., & Pouliakas, K. (2012). Educational segregation and the gender wage gap in Greece. *Journal of Economic Studies*, 39(5), 554–575. https://doi.org/10.1108/01443581211259473

Matthes, B., Christoph, B., Janik, F., and Ruland, M. (2014). Collecting information on job tasks—an instrument to measure tasks required at the workplace in a multi-topic survey. *Journal for Labour Market Research*, 47(4), 273-297. https://doi.org/10.1007/s12651-014-0155-4

Mavromaras, K., Healy, J., Richardson, S., Sloane, P., Wei, Z., & Zhu, R. (2013). A system for monitoring shortages and surpluses in the market for skills. *Report prepared by NILS, Flinders University for the Australian Workforce and Productivity Agency*. http://hdl.voced.edu.au/10707/241984

McGrath, J. (2021). Report on labour shortages and surpluses. European Labour Authority, Publications Office of the European Union. https://data.europa.eu/doi/10.2883/746322

McGuinness, S., Pouliakas, K., and Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys*, 32(4), 985-1015. https://doi.org/10.1111/joes.12254

Mincer, J. (1974). *Schooling, experience, and earnings.* Human Behavior & Social Institutions, No 2.

Nickell, S., & Nicolitsas, D. (1997). Wages, restrictive practices and productivity. *Labour Economics,* 4(3), 201–221. https://doi.org/10.1016/s0927-5371(96)00007-3

OECD (2012), Literacy, numeracy and problem solving in technology-rich environments: framework for the OECD survey of adult skills. OECD Publishing. https://doi.org/10.1787/9789264128859-en

OECD (2022), *'The post-COVID-19 rise in labour shortages'.* OECD Economics Department Working Papers, No. 1721, OECD Publishing. https://doi.org/10.1787/e60c2d1c-en

Pouliakas (2012). The skill mismatch challenge in Europe. In: European Commission (ed.). *Employment and social developments in Europe*. Luxembourg: Publications Office, 351-394. https://data.europa.eu/doi/10.2767/86080

Pouliakas, K., & Wruuck, P. (2022). *Corporate training and skill gaps: did COVID-19 stem EU convergence in training investments?* EIB Working Paper 2022/07. https://www.eib.org/en/publications/economics-working-paper-2022-07

Pouliakas, K., & Russo, G. (2015). *Heterogeneity of skill needs and job complexity: evidence from the OECD PIAAC survey.* IZA Discussion Paper, 9392. https://dx.doi.org/10.2139/ssrn.2672178

Redding, S. (1996) *The low-skill, low-quality trap: strategic complementarities between human capital and R & D. The Economic Journal*, 106 (435), 458-470. https://doi.org/10.2307/2235260

Richardson, S. (2007). *What is a skill shortage?* National Centre for Vocational Education Research. https://files.eric.ed.gov/fulltext/ED495918.pdf

Russo, G. (2017). Skill utilization at work: opportunity and motivation. *IZA World of Labor*, 409-409.

Sattinger, M. (2012), Qualitative mismatches. *Foundations and Trends in Microeconomics,* 8(1–20, 1-168. http://dx.doi.org/10.1561/0700000052

Shah, C., & Burke, G.F. (2005). Skills shortages: concepts, measurement and policy Responses. *Australian bulletin of labour, 31, 44-71.* https://doi.org/10.1016/B978-0-08-044894-7.00778-8

Sostero, M., & Fernández-Macías, E. (2021). *The professional lens: what online job advertisements can say about occupational task profiles.* RePEc: Research Papers in Economics. https://EconPapers.repec.org/RePEc:ipt:laedte:202113

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: looking outside the wage structure. *Journal of labor economics*, 24(2), 235-270. https://doi.org/10.1086/499972

Stevens, M. (1994). A theoretical model of on-the-job training with imperfect competition, *Oxford Economic Papers*, Volume 46, Issue 4, pp. 537–562. https://doi.org/10.1093/oxfordjournals.oep.a042147

Acronyms

ANOVA	Analysis of Variance
BIBB	*Bundesinstitut für Berufsbildung* – Federal Institute for Vocational Education and Training
Cedefop	European Centre for the Development of Vocational Training
COPS	Canadian Occupational Projection System
DG EMPL	Directorate-General for Employment, Social Affairs and Inclusion
DOT	Dictionary of Occupational Titles
DSI	Digital Skills Intensity
ELA	European Labour Authority
ESDC	Employment and Social Development Canada
ESDE	Employment and Social Developments in Europe
ESJS	European Skills and Jobs Survey
ETF	European Training Foundation
EU-LFS	European Union Labour Force Survey
EURES	European Employment Services
EWCS	European Working Conditions Survey
IAB	*Institut für Arbeitsmarkt- und Berufsforschung* - Institute for Labour Market and Occupational Research
ICP	*Indagine Campionaria sulle Professioni* - Survey on Italian Occupations
ICT	Information and Communications Technology
INAPP	*Istituto Nazionale per l'Analisi delle Politiche Pubbliche* - Italian National Institute for Public Policy Analysis
ISCO	International Standard Classification of Occupations
ISTAT	*Istituto Nazionale di Statistica* - Italian National Statistical Institute
JRC	Joint Research Centre
JSA	Jobs and Skills Australia
MAC	Migration Advisory Committee
NCO	National Coordinating Office
NEPS	National Educational Panel Study
NSC	National Skills Commission
OECD	Organisation for Economic Co-operation and Development
OJA	Online Job Advertisements
O*NET	Occupational Information Network
PES	Public Employment Services
PIAAC	Programme for the International Assessment of Adult Competencies
SES	Skills and Employment Survey
Skills-OVATE	Skills Online Vacancy Analysis Tool for Europe
SOL	Shortage Occupation List
SPL	Skills Priority List
STAMP	Survey of Skills, Technology, and Management Practices

Annexes

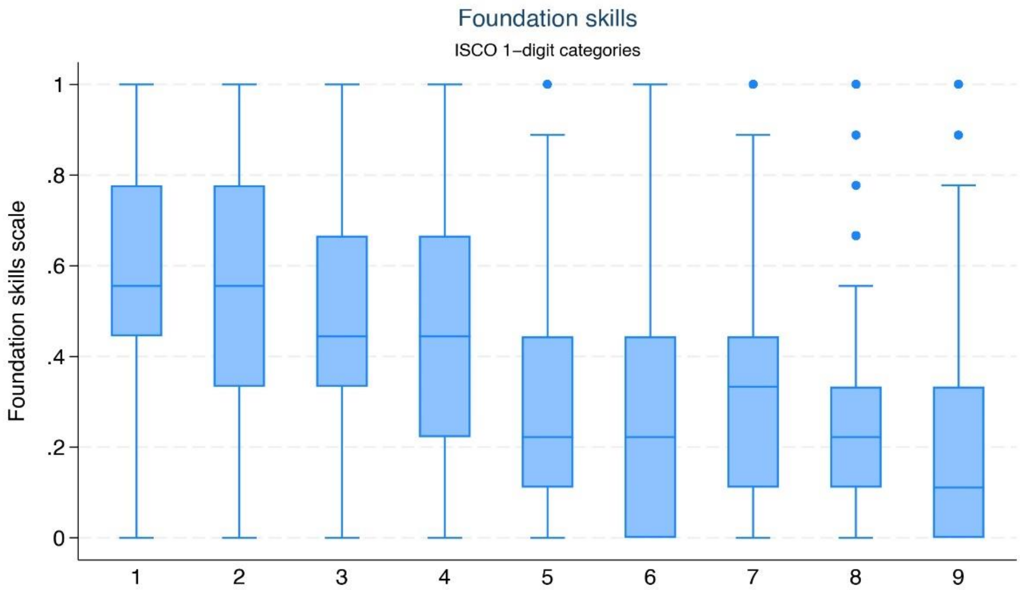
Annex 1. Scales distributions grouped by ISCO 1-digit

The tables and figures (boxplots) below show the distribution characteristics of ESJS2 skill needs and job complexity scales for each ISCO 1-digit occupation, to assess whether the distributions vary across occupation categories.

The foundation and social skill needs scales illustrate a clearly decreasing inter-occupational pattern. Higher levels of social skills than neighbouring middle-skill ISCO groups are observed for services and sales workers, as would be expected, so the interquartile range is narrower compared to the foundation skills scale. While routinisation at work is clearly distinct and higher for medium- to lower-skilled occupations, there is little variation among workers at the medium spectrum of skills. For the job complexity scale the values of skewness and kurtosis are generally increasing across occupation categories.

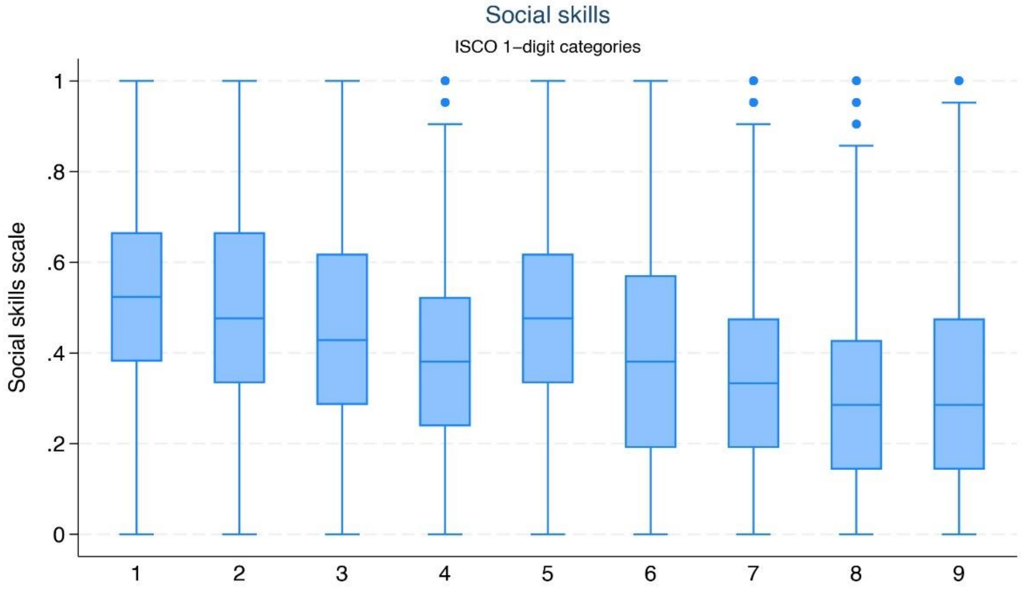
Foundation skill demands scale

	mean	s.d.	skewness	kurtosis	p25	p75	i.q.r.
1 Managers	0.576	0.255	-0.286	2.376	0.444	0.778	0.333
2 Professionals	0.545	0.269	-0.240	2.248	0.333	0.778	0.444
3 Technicians and associate professionals	0.483	0.258	-0.038	2.274	0.333	0.667	0.333
4 Clerical support workers	0.446	0.254	0.065	2.282	0.222	0.667	0.444
5 Service and sales workers	0.298	0.250	0.716	2.780	0.111	0.444	0.333
6 Skilled agricultural, forestry and fishery workers	0.268	0.273	0.933	2.782	0.000	0.444	0.444
7 Craft and related trades workers	0.327	0.254	0.635	2.740	0.111	0.444	0.333
8 Plant and machine operators, and assemblers	0.248	0.219	0.882	3.319	0.111	0.333	0.222
9 Elementary occupations	0.212	0.240	1.245	4.001	0.000	0.333	0.333
Total	0.419	0.282	0.201	2.069	0.222	0.667	0.444
Observations	45329						



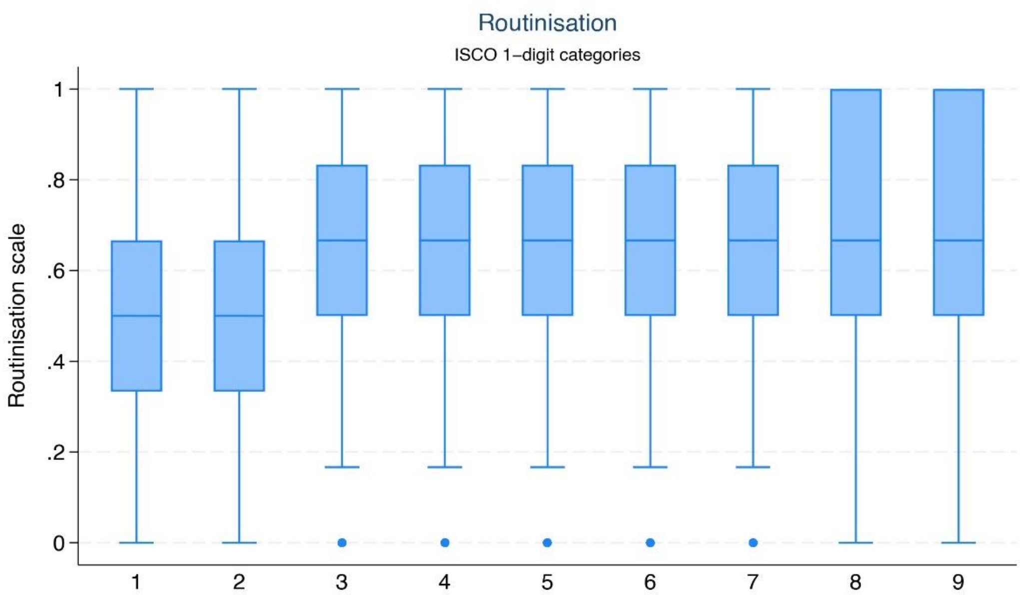
Social skill demands scale

	mean	s.d.	skewness	kurtosis	p25	p75	i.q.r.
1 Managers	0.535	0.216	-0.010	2.552	0.381	0.667	0.286
2 Professionals	0.488	0.222	0.026	2.421	0.333	0.667	0.333
3 Technicians and associate professionals	0.446	0.223	0.192	2.407	0.286	0.619	0.333
4 Clerical support workers	0.395	0.214	0.252	2.566	0.238	0.524	0.286
5 Service and sales workers	0.473	0.222	-0.013	2.508	0.333	0.619	0.286
6 Skilled agricultural, forestry and fishery workers	0.390	0.239	0.213	2.399	0.190	0.571	0.381
7 Craft and related trades workers	0.359	0.209	0.454	2.689	0.190	0.476	0.286
8 Plant and machine operators, and assemblers	0.303	0.193	0.700	3.255	0.143	0.429	0.286
9 Elementary occupations	0.312	0.220	0.549	2.715	0.143	0.476	0.333
Total	0.430	0.228	0.190	2.409	0.238	0.571	0.333
Observations	44979						



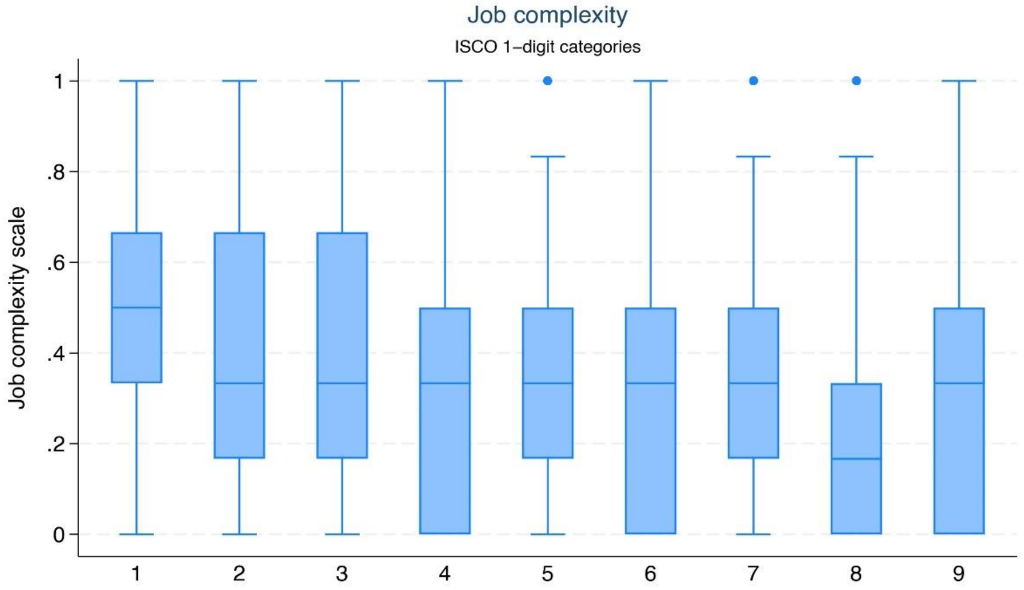
Routinisation scale

	mean	s.d.	skewness	kurtosis	p25	p75	i.q.r.
1 Managers	0.555	0.267	-0.157	2.368	0.333	0.667	0.333
2 Professionals	0.540	0.271	-0.117	2.306	0.333	0.667	0.333
3 Technicians and associate professionals	0.609	0.258	-0.315	2.527	0.500	0.833	0.333
4 Clerical support workers	0.658	0.242	-0.425	2.764	0.500	0.833	0.333
5 Service and sales workers	0.691	0.247	-0.617	2.930	0.500	0.833	0.333
6 Skilled agricultural, forestry and fishery workers	0.686	0.246	-0.490	2.976	0.500	0.833	0.333
7 Craft and related trades workers	0.651	0.256	-0.479	2.684	0.500	0.833	0.333
8 Plant and machine operators, and assemblers	0.713	0.244	-0.649	2.931	0.500	1.000	0.500
9 Elementary occupations	0.724	0.234	-0.616	2.931	0.500	1.000	0.500
Total	0.628	0.263	-0.388	2.525	0.500	0.833	0.333
Observations	44956						



Job complexity scale

	mean	s.d.	skewness	kurtosis	p25	p75	i.q.r.
1 Managers	0.481	0.282	0.102	2.202	0.333	0.667	0.333
2 Professionals	0.450	0.285	0.235	2.272	0.167	0.667	0.500
3 Technicians and associate professionals	0.383	0.285	0.397	2.315	0.167	0.667	0.500
4 Clerical support workers	0.315	0.271	0.642	2.638	0.000	0.500	0.500
5 Service and sales workers	0.339	0.286	0.579	2.489	0.167	0.500	0.333
6 Skilled agricultural, forestry and fishery workers	0.344	0.300	0.600	2.378	0.000	0.500	0.500
7 Craft and related trades workers	0.365	0.280	0.501	2.496	0.167	0.500	0.333
8 Plant and machine operators, and assemblers	0.274	0.270	0.874	3.062	0.000	0.333	0.333
9 Elementary occupations	0.300	0.282	0.724	2.653	0.000	0.500	0.500
Total	0.374	0.288	0.443	2.339	0.167	0.667	0.500
Observations	45172						



Annex 2. ANOVA analysis

The between variation measures how much the group means differ among each other, while the within variation measures, within each group, how much the observations vary from their group mean. The sum of the two components equals the total variation.

In brief, the analysis is based on the following measures:

Total sum of squares	$SS.TOT = \sum_{ij} (y_{ij} - \bar{y}_{..})^2$	total variation
Treatment sum of squares	$SS.T = \sum_{i} n_i(\bar{y}_{i.} - \bar{y})^2$	between variation
Error sum of squares	$SS.E = \sum_{...} (y_{ij} - \bar{y}_{i.})^2$ $SS.TO = SS.TR + SS.E$	within variation
	$SS.TO = SS.TR + SS.E$	
	$F = \frac{MS.T}{MS.E}$ $\quad MS = \frac{SS}{df}$	

The ratio between the two components is based on the mean squares (MS), which are calculated dividing the sum of squares (SS) by their respective degrees of freedom (df). In detail, the F ratio equals the ratio between the treatment mean square and the error mean square.

The value of the ratio allows determining whether there is a significant difference due to the treatment. Large values of F support the hypothesis that not all mean values are equal, meaning that a significant percentage of the total variation is explained by the between variation, that is the deviation of treatment means around overall mean.

The ANOVA can therefore provide a measure of how much the occupational groups vary between them with respect to each of the scales considered. The analysis can be performed both at ISCO 1-digit level and at a more detailed level, considering ISCO 4-digit occupations. This allows one assessment of the extent to which the variation in job-skill requirements in ISCO1 broad occupational groups is driven by between or within differences in narrow ISCO4 occupations.

Annex 3. Measuring labour and skill shortages

Table A3. **Measuring labour and skill shortages**

Measurement approaches	Indicators
Single indicator approach: **<u>national level</u>**	• Unemployment rate • Unemployed gap (unemployment relative to NAIRU) • Underemployment rate (Bell and Blanchflower, 2019) • Share of unemployed to employed by education level • Coefficient of variation of employed relative to unemployed • Ratio of vacancies to unemployment (EC, 2014a,b) • Ratio of new hirings to unemployment (EC, 2014a,b) • Ratio of job hirings to job separations; calibration of matching efficiency • Hard to fill vacancies • Difficulties filling jobs (Manpower talent survey) (Cedefop, 2015a) • Skilled labour is readily available (IMD World Competitiveness Yearbook; Cedefop, 2015a) • % manufacturing firms where 'labour is a factor limiting production' (European Commission, 2023) • Skill mismatch index (SMI) - distance between the relative demand and supply of a given skill j, where demand is captured by the share of employed persons with skill j in the economy at a given time period and supply is approximated by the share of the active workforce in possession of a given skill level (or, similarly, the stock of unemployed workers with skill level j) (Pouliakas, 2012). • Length of time to fill vacancies (Haskel and Martin, 1993)

Measurement approaches	Indicators
Single indicator approach: <u>industry/occupation level</u>	• Occupational SMI: measure of the relative dispersion of the employment share across the nine occupational groups (based on ISCO). It is calculated as the sum, over nine occupational groups, of the absolute difference between the share of an occupational group in employment and their (potential) share in the working age population (European Commission, 2022). • Difficulties filling jobs (Manpower talent survey) • Difficulties finding right skills (European Company Surveys; EIB Investment surveys) (Cedefop, 2015a, 2018; Pouliakas and Wruuck, 2022) • Hard to fill vacancies • Change in employment by occupation and education level • New hirings growth (EC, 2014) • (Rising) returns to education • Ratio of vacancies to unemployment in region, industry or (past) occupation, relative to average ratio in economy (Lazear and Spletzer, 2012)
Other (indirect) proxies	• Rising levels of underskilling at hiring across cohorts (Cedefop, 2015a, 2018) • Rising difficulties finding skills combined with falling training investments (Pouliakas and Wruuck, 2022) • Employment permits/visas

Measurement approaches	Indicators
Composite indicator approach	• Combination of employment growth, new hirings growth and stock of new hirings by industry/occupation (EC, 2014) • List of mismatch/shortage occupations formulated following quantitative analysis of labour market indicators that are proxies of labour market disequilibrium/pressure 'at the margin'; based on wide set of indicators capturing labour market pressures/tensions e.g. recruitment/job vacancy data/graduation flows, as well as markers of regulation/licensing or visa permits in occupations (Mavromaras et al., 2013) • Range of employer-based indicators (e.g. skill shortage vacancies as % of hard-to-fill vacancies), price-based indicators (e.g. change in mean hourly pay, returns to occupation), volume-based indicators (e.g. % change in unemployment by sought occupation, change in employment, change of median total paid hours, change in % of new hires) and indicators of imbalances (e.g. change in median vacancy duration, unfilled vacancies/unemployment by sought occupation) (UK MAC) • List of 'Mismatch priority occupations', based on four key indicators used as proxies of labour market tensions: degree of over or under-qualification within the occupation; change in employment in the occupation over time; changes in wages within the occupation over time; and workers' participation in training within the occupation. For each of the factors, the changes or levels are examined relative to the overall (all occupation) averages within a country. Changes over time are investigated for a given time period (e.g. last five or ten years). Information on the different factors is combined so that higher values of a ranking indicator (which combines the four factors) would be indicative of likely skills shortages whereas lower values suggest skills surpluses. All 3-digit ISCO occupations were ordered by their value on this ranking indicator and the top 20-30 occupations were provided for further examination and validation by country experts (Cedefop, 2016). • OECD Skills for Jobs Database, which links the indicators approach to deriving occupational shortages (based on indicators of wage growth, employment growth, hours worked growth, the unemployment rate and under-qualification growth) with O*NET data, and, more recently, with Burning Glass OJA data, to derive genuine measures of shortages in 'skills (OECD, 2022) • Machine learning approach to predicting labour shortages for occupations by utilising a series of labour demand and labour supply occupational indicators. Key lessons of this research are that labour shortages exhibit strong autoregressive properties, implying that good indicators should aim to include lagged values of indicators; and job ads are the most predictive feature for pre-empting yearly labour shortage changes for occupations (Dawson et al., 2020).

Source: Authors' own elaboration.

Annex 4. List of occupational skill shortages

Table A4. **List of occupational skill shortages**

ELA- EURES 2022	
ISCO 4-digit code	***Most often reported shortage occupations, including high magnitude shortage occupations***
7112	Bricklayers and related workers /
7115	Carpenters and joiners
8332	Heavy truck and lorry drivers
7223	Metal working machine tool setters and operators
2221	Nursing professionals
7126	Plumbers and pipe fitters
7411	Building and related electricians
7212	Welders and flame cutters
7114	Concrete placers and finishers etc.
7213	Sheet-metal workers
7122	Floor layers and tile setters
2512	Software developers
5120	Cooks
9313	Building construction labourers
7412	Electrical mechanics and fitters
2514	Applications programmers
2211	Generalist medical practitioners
8331	Bus and tram drivers
7231	Motor vehicle mechanics, repairers
2212	Specialist medical practitioners
2519	Software, applications developers
8342	Earthmoving and related plant operators
5131	Waiters
2342	Early childhood educators
7214	Structural metal preparers and erectors
7131	Painters and related workers
7233	Agricultural and industrial machinery mechanics and repairers
7512	Bakers, pastry-cooks, confectionery makers
2511	Systems analysts

7511	Butchers, fishmongers and related food preparers
5321	Health care assistants
9112	Cleaners and helpers in offices, hotels
3113	Electrical engineering technicians
2634	Psychologists
7123	Plasterers
2142	Civil engineers
2264	Physiotherapists
7121	Roofers
European Commission Directorate-General for Employment, Social Affairs and Inclusion (DG EMPL) Employment and social developments in Europe (ESDE) 2023	
ISCO 3-digit code	***Description of persistent shortage occupations***
221	Medical doctors
222	Nursing and midwifery professionals
251	Software and applications developers and analysts
512	Cooks
513	Waiters and bartenders*
522	Shop salespersons
532	Personal care workers in health services
711	Building frame and related trades worker
712	Building finishers and related trades workers
721	Sheet and structural metal workers, moulders and welders, and related workers
723	Machinery mechanics and repairers
741	Electrical equipment installers and repairers
833	Heavy truck and bus drivers
911	Domestic, hotel, and office cleaners and helpers

Source: ELA (2023); European Commission (2023)

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