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DISCUSSION PAPER SERIES

IZA DP No. 18133

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ABSTRACT

Developing a New European Indicator of Potential Skill Shortages*

Skill shortages are a type of skill mismatch whereby employers are unable to fill existing vacancies due to a lack of suitably qualified and/or skilled candidates. Despite representing a significant concern for policy makers, both at national and EU level, the literature on skill shortages is hugely underdeveloped. The absence of research in this area has resulted in a lack of clarity and consistency on how skill shortages are defined and measured. In this study, using data from the 2021 European Skills and Jobs Survey combined with Lightcast job vacancy data, we attempt to bridge the methodological gap by developing a measure of potential skill shortages that can be readily replicated across countries over time. We estimate that approximately 2% of job vacancies in the European Union are likely to experience skill shortages. However, there is substantial variation across occupations, ranging from 5.1% for ICT professionals to approximately zero in more elementary occupations. There is also substantial variation in the estimated incidences of potential skill shortages at member state level, ranging from over 10% in Luxembourg to under 1% in Estonia and Poland. Our analysis also shows that occupations that are most likely to experience skill shortages also tend to experience relatively high rates of changes in skill requirements over time.

JEL Classification: J6, J20, J22, J23
Keywords: skill shortages, measurement, policy

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1. Introduction and Existing Literature

Skill shortages describe a situation whereby employers are unable to fill existing vacancies due to a lack of suitably qualified and skilled external candidates. Skill shortages have the potential to inhibit firm level productivity and, if pervasive enough, can negatively feed through to macroeconomic variables such as economic growth and wage inflation. However, despite the fact that it is common to see policies implemented at both a national and European level to combat skill shortages, there is remarkably little empirical research on their impacts (McGuinness et. al, 2018) and even less agreement on how to measure the phenomenon. The scarcity of evidence related to skill shortages is demonstrated in McGuinness et al. (2025), which summarise the skill mismatch peer reviewed literature published between 2006 and 2022, with just 14 studies on skill shortages published over a 16-year period. According to McGuinness et al. (2025), skill shortages account for just 5 per cent of the skills mismatch literature. However, despite the sparsity of the research base, skill shortages remain the principal concern of policy makers in the realm of skill mismatches. This paper reviews the existing methodological approaches to measuring skill shortages before going on to propose an empirical measurement approach that we believe will effectively capture potential skill shortages in a way that can be easily replicated across countries and over time.

As previously mentioned, the evidence regarding impacts of skill shortages is thin and somewhat mixed. Few studies have been able to measure the impact of skill shortages on companies proving that they negatively impact firms' productivity (Bennett and McGuinness, 2009; Tang and Wang, 2005; Haskel and Martin, 2006; Forth and Mason, 2006; Mason et al., 1994; Sharma et al., 2016). Other studies proved that skill shortages negatively affect R&D investments and innovation projects (Nickell and Nicolatsis, 1997; Horbach and Rammer, 2022). Other studies find no evidence that skill shortages negatively affect firms' performance, measured in terms of sales (Healy et al., 2015). A key conclusion that we can take away from this literature is that the lack of measurement consistency across studies makes it extremely difficult to draw concrete conclusions regarding the impacts of skill shortages.

This study is more closely aligned to another strand of literature that seeks to measure skill shortages. As organisations and policymakers strive to align workforce capabilities with evolving market demands, the accurate identification and quantification of skills shortages have become increasingly important. The accurate and consistent measurement of skill shortages is vital to ensure well-informed policy measures. Within the literature, there are two main approaches to measuring skill shortages: (1) **Employer-Reported (subjective) Data**: containing subjective measures of skills shortages or gaps, offering valuable first-hand insights into workplace challenges, and (2) **Objective Indicators**: which bring together various statistics and data to develop generally indirect measures of skill shortages.

Table 1 reports the studies that use subjective methodologies; specifically, we report the firm-level survey data used in the studies, and the specific questions asked to employers on skills shortages. The first thing that becomes apparent is that no two survey approaches adopt the same measurement approach. Some surveys ask only about hiring difficulty without directly quantifying the shortages (Ho, 2016) and in instances where skill shortages are referred to they are associated with varying definitions of recruitment difficulty, e.g. difficult to hire (Tang and Wang, 2005), hard-to-fill vacancies (Watson et al, 2006, Gambin et al, 2016; Horbach and Rammer, 2019) unfilled vacancies (Bellman and Hubler, 2014; Sharma et al, 2016; Horbach and Rammer). Some measurement approaches set various time parameters (i.e., online vacancy duration) around the skill shortage (Watson et al. 2006; Healy et al.2015; Sharma et al., 2016; Weaver and Osterman, 2017; Chang-Richards et al, 2017; Beerli et al., 2020) while others do not (Tang and Wang, 2005; Bellmann and Hübler, 2014; Gambin et al. 2016; Ho, 2016; Mergener and Maier, 2019; Horbach and Rammer, 2022). In general, despite the lack of consistency, subjective, firm-level survey measures are an important source of information as they are a primary indicator of skill shortage. They are, however, associated with a number of weaknesses including potential measurement error whereby employers wrongly attribute hiring difficulties to skill shortages. Other, non-skill related factors influencing hiring difficulties include unattractive working conditions, uncompetitive wages and ineffective Human Resource Management (HRM) processes. The existing limited evidence suggests that these biases are likely to be substantial. Drawing on the Eurobarometer Flash Survey 304, Cedefop (2015b) shows that while 47 per cent of employers report difficulties in recruiting suitably skilled graduates, the total proportion of graduate employers deemed to be facing genuine skill shortages was 12 per cent.

With significant advances in data analysis techniques, such as web scraping, artificial intelligence and big data analytics occurred over the last years, the use of objective methodologies that capture skill shortages has become increasingly widespread. Such objective methodologies aim to provide quantifiable and data-driven insights into labour market dynamics and potential skill shortages. Objective approaches mainly employ job vacancy data; however, they also use various indirect indicators (such as unemployment, wages, undereducation etc.) to gauge labour market tightness and potential skill shortages. Some of the key examples of objective measures published are presented in Table 2.

A recent objective indicator that attempts to providing a cross-country measure of skill shortages has been developed by the OECD (OECD (2017, 2018, 2022). The OECD 'Skills for Jobs' database stands as the most prominent example of more comprehensive objective method used to assess skill shortages. The OECD employs a two-step methodology:

- Step 1: Identifying occupational imbalances – the initial step involves calculating an ‘Occupational Shortage Indicator’ for 33 occupational groups at the ISCO-08 2-digit level. This indicator ranks occupations based on whether they are facing shortages or surpluses in a given country. To do this, five sub-components are analysed and compared to the economy-wide trends: wage growth, employment growth, hours worked growth, unemployment rate and change in under-qualification by occupation. To minimise the impact of conflicting signals from any single sub-component, a composite indicator is used. Weights are applied to each sub-component, with all sub-components, except employment, receiving equal weight. Employment is assigned to a smaller weight (half) due to its lower explanatory power. The result of this analysis provides a ranking of occupations from those most in shortage to those most in surplus.

- Step 2: Determining skill shortages and surpluses – The Occupational Shortage Indicator, calculated in the first step, is then used to analyse the underlying skill / competency requirements of the occupations in shortage. This process leverages data on skill requirements for various occupations, with the values from the Occupational Skill Shortage Indicator used to weight the importance and level of skill requirements associated with each occupational group. The OECD indicator is therefore designed to identify the occupations and skills that are in shortage within a particular country.

The ILO (2020) published long-term projections for ICT skill shortages in Canada, Germany, China and Singapore, developed through models based on various assumptions that, ultimately, compare labour supply and demand. The ILO study summarises the current forecasting methods employed in these four countries and publishes estimates of projected ICT skill shortages. Despite these various efforts, the ILO report highlights challenges in accurately measuring skill shortages, stemming from differing definitions of 'ICT specialists' across countries, the lack of detailed and comparable data, and the rapid pace of technological change. Other examples of the construction of objective measures of skills shortages include Gambin et. al (2016) for the UK, Dawson et. al (2019) for Australia, Hertrich and Brenner (2024) for Germany and Aksenova et al. (2024) for the EU countries. It is also worth noting that in 2024 Cedefop launched their European Skills Index (ESI), which is designed to measure the performance of skills formation and matching systems within EU member states. While the index is not designed to measure the incidence of skill shortages and gaps, it will at least partially reflect these.

As was the case with the subjective indicators, a key weakness of the objective approaches is a lack of consistency in the measurement methodology and, with some notable exceptions, the indicators tend to be country-specific and not easily replicable for multiple countries. There is also a good deal of subjectivity associated with some of the indicators selected as potential drivers of skill shortages, and it is unclear the extent to which selected indicators are actually related to the key outcome variable. Changes in these indicators can be driven by factors beyond skill availability, such as broader economic trends, changes in labour market regulations or technological disruptions all of which will be related to skill shortages to varying degrees. This complexity necessitates sophisticated statistical analysis and careful control of multiple variables to establish meaningful correlations between observed patterns and actual skill shortages. However, it is almost impossible to ascertain the extent to which such objective approaches are generating accurate estimates of skill shortages. Another limitation of objective methodologies for estimating skill shortages, as acknowledged by Dawson et al. (2019), is their focus on labour demand data and the reliance on proxies to estimate labour supply. This approach is unlikely to capture the complete picture of skill shortages in the labour market. Furthermore, the use of online job postings as a primary data source introduces potential biases in skill requirement analysis. Employers utilising online platforms might disproportionately seek candidates with specific skill sets, which may not accurately reflect the skill sets required across all positions within an occupation. Also, extended vacancy durations, which have been used as inputs to some measures, may result from internal factors unrelated to genuine skill shortages, such as unattractive wages or inefficient recruitment practices. These confounding variables can potentially lead to an overestimation of actual skill shortages in the labour market.

Table 1: Summary of Employer based Skill Shortages- Subjective Measures

Year	Author(s)	Data used	Country	Sector	Actual question for skill shortages
2005	Tang and Wang	Statistics Canada Survey of Innovation	Canada	Manufacturing	*It is difficult to hire qualified staff and workers; It is difficult to retain qualified staff and workers*
2006	Watson et al.	1998 Dorset Employer Survey	UK	Various	*Did you experience hard-to-fill vacancies due to skill shortages in the past 12 months?*
2014	Bellmann and Hübler	IAB Establishment Panel Survey	Germany	Various	*How many unfilled qualified jobs does your firm have?*
2015	Healy et al.	Business Longitudinal Database	Australia	SMEs	*Did this business have skill shortages during the last year?*
2016	Gambin et al.	UK Employer Skills Survey	UK	Various	*Hard-to-fill vacancies; Skill shortages vacancies*
2016	Ho	Survey administered by the author(s)	Hong Kong	Construction	*Indirectly assessed through expert consensus on the existence and severity of skill shortages*
2016	Sharma et al.	Survey administered by the author(s)	Australia	Various	*How many unfilled job vacancies have you encountered over the preceding 12 months?*
2017	Weaver and Osterman	Survey administered by the author(s)	US	Manufacturing	*How many core production worker vacancies have persisted for three months or more?*
2017	Chang-Richards et al.	Survey administered by the author(s)	New Zealand	Construction	*Have you experienced a shortage for specific skills in your company since the earthquake?*
2019	Mergener and Maier	Survey administered by the author(s)	Germany	Various	*What are your expectations regarding future recruitment difficulties?*
2020	Beerli et al.	Swiss Employer Survey	Switzerland	Various	*Have your innovation efforts been negatively affected by a shortage of specialised personnel in the last year?*
2022	Horbach and Rammer	Community Innovation Survey	Germany	Various	*How many job vacancies could not be filled or hard to be filled with workers lacking the desired qualifications?*

Note: The actual questions presented are either directly extracted from the papers or have been indirectly inferred based on the authors' descriptions.

Table 2: Summary of Studies on Skill Shortages- Objective Measures

Year	Author(s)	Data used	Country	Sector	Measures Used
2016	Gambin et al.	Labour Force Survey, Annual Survey of Hours and Earnings	UK	Various	Employment and unemployment rates, wage levels and occupational skill profiles
2019	Dawson et al.	6.7 million Australian online job ads (2012-2019)	Australia	Data Science and Analytics	Skill co-occurrence patterns, DSA skill intensity, Relative Comparative Advantage (RCA)

2020	ILO	Canada's ESDC; Germany's BiBB and IAB; Singapore’s skills framework; China’s CCW	Canada, Germany, Singapore, China	ICT	Long-term labour market forecasts, labour supply and demand projections
2024	Hertrich and Brenner	Federal Employment Agency job vacancy data	Germany	Skilled workers, specialists, experts	Average vacancy time (days), spatial vector autoregressive (VAR) model
2017, 2018, 2022	OECD	Skills for Jobs database, Lightcast (EBG) data	OECD, EU countries	Various sectors, with a focus on ICT and digital skills	Occupational Shortage Indicator, skill imbalance index, RCA
2024	Aksenova et al.	OECD Skills for Jobs, Eurostat ICT data (2011-2021)	34 European countries	Digital skills, ICT	Paired regression analysis, skill shortage indicators, growth rate of ICT specialists

Note: The measures are directly extracted from the papers.

2. Methodology

We attempt to develop an indicator of potential skill shortages using an approach that (a) is built on job characteristics that can reasonably be associated with a skill shortage and (b) can be easily replicated for all countries across time. To do this, we employ an objective measurement approach using online job vacancy data, that is benchmarked to a subjective measurement approach using survey data with detailed job characteristics. Our approach is multi-dimensional, as it employs a broad set of variables, and we identify and impose several conditions / job characteristics that are likely to be associated with potential skill shortages within the two different datasets.

First, we use data from the 2021 European Skills and Jobs Survey (ESJS), which is a broad employee-based survey on adult employees aged 24 to 65 in the EU countries, plus Iceland and Norway, with a total sample of over 46,000 observations. The 2021 European Skills and Jobs Survey is the second wave of the survey administered by Cedefop.. It provides workers’ sociodemographic information as well as detailed job characteristics on skill requirements and task content, wages and job satisfaction. We identify several job characteristics that are likely to be associated with potential skill shortages at an occupational level (at ISCO 2-digit) and calculate the share of jobs that are likely to be difficult to fill, at an EU level and at member state level. It should be noted that the ESJS2 approach effectively measures the proportion of jobs that are likely, in our view, to be difficult to fill, should openings become available to the labour market.

Second, we employ 2021 job advertisement data from Lightcast. Lightcast is a private labour market analytics company that aggregates millions of job advertisements worldwide on a daily basis; they extract over 50 elements from the job postings descriptions and classify them according to standard labour market classifications. In a similar manner to our use of the ESJS, we identify several characteristics that are likely to be associated with difficult to fill vacancies and the proportion of jobs in each ISCO category that are difficult to fill across the EU and at member state level. Therefore, our approach will measure the proportion of current vacancies that we estimate will be hard to fill. While the Lightcast measure is solely demand-based, and may not precisely reflect the skill requirements of jobs, it is replicable over time.

We then validate our Lightcast approach against the ESJS estimates to ensure that our skill shortage measure based on vacancy data broadly reflects the current distribution of skills and jobs actually employed within the labour market and helps to ensure that any policy measures designed on the basis of job vacancy estimates will be more likely to align with actual labour market needs. We validate our Lightcast approach by calculating the correlation between the potential skill shortage estimates in the two datasets within 2-digit ISCO occupation. As a further robustness check, within Lightcast data, we also introduce a measure for changing skill requirements, based on work by Redmond, Kelly and Brosnan (forthcoming) and Deming and Noray (2020), to confirm that potential skill shortages are more likely to appear in occupations where skills demand has been evolving more quickly over time. Finally, following our validations, we estimate the share of potential skill shortages at 2-digit ISCO level for the EU and for all member states for 2022 and 2023 using Lightcast data. The benchmarking of an objective measurement approach to a dataset reflecting the current distribution of skills and competencies being utilised within the labour market is, in our view, a substantial advancement in the measurement of skills shortages at both a national and European level.

2.1 The European Skills and Jobs Survey (Wave 2)

Within the 2021 European Skills and Jobs Survey, we identify and impose several conditions/job characteristics that are likely to be associated with potential skill shortages. We develop a set of indicators that capture explicit measures of job complexity, competency and experience requirements as well as higher wages. In order to distinguish skill from labour shortages, for many of our indicators we set the condition that various metrics exceed both the respective occupational average and the economy wide average. This implies that jobs with a relatively low skill content that lie above their occupational average are not identified as potential skill shortages.

The rationale for our approach is that genuine skill shortages should only appear in jobs with specific characteristics. For example, a job that has little complexity and requires very few skills is unlikely to be associated with a genuine skill shortage. By definition, a skill shortage implies that an employer cannot recruit a candidate with the required skills. If the job itself does not require complex skills, then genuine skill shortages should not be present. Of course, employers may sometimes find it difficult to recruit candidates for low-skilled and low-wage jobs, but this is likely not due to the pool of potential candidates not having the skills required to do the job. Rather, it may simply be that potential employees are unwilling to work in such a role at the advertised pay and conditions. Therefore, in order to be identified as an area of potential skill shortage, a job must meet each of the following criteria:

1. **Complex job within occupation:** One would expect that the higher the level of skill complexity of the job, the higher the likelihood for employers to have difficulties in recruiting a qualified candidate. We construct a composite index that attempts to identify more skill-complex jobs within occupations. Specifically, we look within ISCO 2-digit occupations to identify jobs within that classification that are of greater complexity than the average. We do this by taking into account several variables that relate to the use of foundational skills within the jobs. In the survey questionnaire, employees are asked to rate their level of intensity in using reading, writing and math skills while doing their job (low, intermediate and high level of skills use). Dummy variables are derived for each of the three foundational skills. For example, 'intermediate reading' is a dummy variable that takes value one if the respondent reported an intermediate intensity in using reading skills, zero otherwise. For each respondent (i), the foundational index is the sum of intermediate and high level of foundational skills and ranges from 0 to 6[1]:

$$FoundationalIndex_i = IntermediateReading_i + HighReading_i + IntermediateWriting_i + HighWriting_i + IntermediateMath_i + HighMath_i \tag{1}$$

   We compute the average value of the index at an ISCO 2-digit occupational level. When the value of the index is higher than the average calculated at occupational level, the job has a high level of complexity, and it is considered to have met a requirement for being a potential skill shortage.

2. **Economy-wide complex job:** In our analysis, we also want to take into account complex jobs within the general economy, not only at an occupational level. Therefore, we compute the average value of the foundational index (i.e. Parameter 1 above) at the country level. When the value of the index for respondent i is above the average calculated at country level, the job is considered to be a complex job within the general economy / labour market, it is deemed to have met a requirement for being a potential skill shortage.

3. **High volume of task requirements within occupation:** One would expect that the higher the volume of task requirements required by a job, the higher the likelihood for employers to have difficulties in recruiting a qualified candidate. We constructed a composite task index that incorporates up to 17 tasks, using work organisation variables, creative tasks variables and digital skills variables.

[1] The variables used are C_READ5P, C_READ25P, C_WRITE5P, C_WRITE25P, C_MATHMED and C_MATHADV.

In the questionnaire, employees are asked several questions related to their work planning tasks. The question states: '*How often does your main job involve the following activities?'*. The tasks include: *choosing the methods or tools of your work*; *planning your work activities; reacting to situations that could not be anticipated; working on varying assignments; learning new things,* with respondents rating one if rarely or never, up to four if often and very often. Employees are also asked *'How often did you do any of the following activities as part of your main job in the last month?'.* The tasks include: *try to develop or create new or improved products or services; try to develop new or improved ways of doing your work*, with respondents rating from one if rarely or never, up to four if often and very often.

We also incorporate a digital task index variable within our task index. In the questionnaire, employees are first asked whether or not they use any computing devices to do their job (i.e., desktop computer, laptop / notebook computer, tablet computer and smartphone). Individuals reporting using these devices are asked *'Did you use any of the computing devices from the previous question to do the following activities as part of your main job in the last month?'*. The questionnaire provides a very broad and comprehensive list of ten digital activities: from basic activities such as browsing the internet, writing and using Word, preparing presentations on PowerPoint and using simple excel functions Excel; to medium-intensity activities such as using advanced Excel functions, working with specialised, sector or occupation-specific software, and managing databases with SQL; to high-intensity activities such as coding with C++, Python and Java, writing programs using AI methods and developing or maintaining IT systems. The ten dummies related to each digital activity are then recoded accordingly into a categorical digital index, ranging from 0 (non-user), to 1 (basic use), 2 (medium use) and 3 (high use) of digital skills. Our composite tasks[2] index is the sum of work organisation variables, creative tasks variables and digital skills variables[3]: We compute the average value of the task index at an ISCO 2-digit occupational level. When the value of the index is higher than the average calculated at occupational level, the job has a high number of tasks, and it is considered to have met a condition for being a potential skill shortage.

4. **Economy- wide high task requirement:** In our analysis, we also want to take into account jobs with high task requirements within the general economy, not only at an occupational level. Therefore, we compute the average value of the task index

[2] Task index = choosing methods + planning activities + react to unexpected + working on varying assignments + learning new things + create new products + improve methods + basic digital skills+ medium digital skills + high digital skills

[3] The variables used are B_RTAUT, B_RTPLAN, B_RTEXP, B_RTVAR, B_RTLRN, C_CREAPRD, C_CREAMET, D_PC_CAT_WEB, D_PC_CAT_WORD, D_PC_CAT_PPT, D_PC_CAT_SHEET, D_PC_CAT_SPEC, D_PC_CAT_MACRO, D_PC_CAT_BASE, D_PC_CAT_PGR, D_PC_CAT_AI, D_PC_CAT_SYS.

at described above at country level, and when the value of the index is above the average calculated at country level, the job is considered to be a hight task demanding job within the general economy/labour market, and the job has met a condition for being a potential skill shortage.

5. **Long tenure:** As an experienced workforce is limited, and intermediate/senior positions require more experience than entry-level positions, it is more likely that skill shortages arise among intermediate/senior level positions, compared to entry-level positions Therefore, we impose the condition that jobs with tenure longer than one year are likely to be considered potential skill shortages.

6. **High wage within occupation:** If employers experience difficulties in recruiting qualified candidates for their vacancies, they may have to raise the salary in order to attract applicants. Presumably, a high wage is also proxying high job complexity. Therefore, jobs that are associated with skill shortages are likely to also have a higher-than-average wage. We compute the average monthly net wage at an ISCO 2-digit occupational level. When an employee's monthly net wage is higher than the average calculated at occupational level, the job is considered to have met a condition for being a potential skill shortage.

7. **Economy wide- high wage:** We also want to take into account jobs with higher-than-average wage within the general economy, not only at an occupational level. Therefore, we compute the average monthly net wage at country level; when an employee's monthly net wage is above the average calculated at country level, the job is considered to be a potential skill shortage.

When all seven conditions above hold simultaneously, a job is identified as a potential skill shortage within the 2021 European Skills and Jobs Survey.[4]

2.2 Lightcast Data

While the ESJS provides insights into the experiences of employees in the European labour market (labour supply), it is equally important to understand skills shortages from the perspective of employers (labour demand). As stated, the key advantage of developing a measure of potential skill shortages using this data is that estimates can be updated annually as new Lightcast data is published, and, due to the large sample sizes involved, replicated for individual member states. This considered, we use online job vacancy data from Lightcast (formerly Burning Glass Technologies) to identify potential skill shortages using metrics that, as far as is possible given the differences in the datasets, correspond to those set in the ESJS data.

[4] Note that in our analysis we exclude armed force and agricultural occupations (Armed Forces; Skilled agricultural, forestry and fishery workers; Agricultural, forestry and fishery labourers).

Lightcast collects job vacancy data from numerous online billboards and websites, parsing vacancies into ready-to-use data for analysis. Their data collection tools extract more than 50 elements from each job posting. Where available, each job posting contains information such as the corresponding sector (NACE), region (NUTS), occupation (ISCO), skill requirements (ESCO), geographical location, company name, type of contract, working arrangement (full-time/part-time), remote working arrangements, salary, educational requirements, experience and skill requirements. We use vacancy data for the EU-27 plus UK from 2021 to identify potential skill shortages (or "difficult-to-fill positions") in the labour market. We select data from 2021 to be time-consistent with the data collection for the ESJS, so that we analyse labour supply and labour demand over the same period of time.

We adopt a similar approach to our classification of skills shortages using the ESJS, in that we identify specific job vacancy conditions that are likely to be associated with potential skill shortages. Specifically, six criteria – relating to required competencies, experience requirements, salary requirements and vacancy duration – must all be met. These criteria are outlined in turn below.

1. **High competency requirements within occupation:** We consider a vacancy to be a potential shortage if a vacancy contains an above average (mean) number of competency requirements within its relevant occupational category. This is measured as the average number of technical skill requirements per-vacancy within each ISCO 2-digit occupation. The underlying assumption is that vacancies that require a high number of competencies employers are more likely to experience difficulties in recruiting a qualified candidate.

2. **Economy wide high competency requirements:** We also consider a vacancy to be a potential shortage if a vacancy contains an above average (mean) number of competency requirements in their respective national economy. This is measured as the average number of skill requirements per-vacancy at the country level. The underlying assumption is that vacancies that post more skill requirements are comparatively less likely to be filled by applicants with a suitable skillset than vacancies with less competency requirements. This condition ensures that we are excluding vacancies with competency requirements that exceed the occupation mean but are below the average for the labour market as a whole. It is unlikely that such vacancies will be particularly difficult to fill.

3. **Previous Experience:** Similar to the ESJS condition, since skill shortages are more likely to occur among experienced workforces, rather than among entry level positions, we consider a vacancy to be a potential skill shortage if it requires at least one year of experience.

4. **High wage within occupation:** Similar to the ESJS condition, if employers experience difficulties in recruiting qualified candidates for their vacancies, then this is likely to be reflected in a higher salary. We consider a vacancy to be a

potential skill shortage if a vacancy posts a higher-than-average salary in the corresponding ISCO 2-digit occupation.

5. **Economy wide- high wage:** We also want to take into account jobs with a higher-than-average posted salary within the general economy, not only at an occupational level. Therefore, we consider a vacancy to be a potential skill shortage if a vacancy posts a salary higher-than-average computed at country level. This condition is set in order to exclude potential labour shortages, which may have above average wages for the occupation, from potential skill shortages.

6. **Duration Condition:** We consider a vacancy to be a potential shortage if the job vacancy remains published for a duration greater than 30 days (and less than 120 days for reasons discussed below). This is based on the assumption that firms will seek to fill job vacancies as quickly as possible, subject to the constraint of the quality of applicants. In a scenario where companies struggle to find suitable qualified candidates, the vacancies will remain online for longer. This means that vacancies with longer durations are more likely to be associated with potential skill shortages. There is some concern that the Lightcast data may simply report the duration of the advertisement rather than the duration of the vacancy. However, our approach will at least allow us to separate out those vacancies that have not been filled quickly (i.e., within 30 days).

In summary, positions with high skill requirements both at an occupational level and at country level, that require experience, that post above-average salaries both within occupation and within an economy and are published online for extended periods of time are associated with potential skill shortages / hard-to-fill vacancies. Where all six of these conditions apply to job vacancies, we identify them as potential skill shortages.

We apply the following restrictions to the Lightcast data for the purpose of analysis. First, we only include data where both salary information and experience requirements are available. Second, we only include data for which at least one “Hard Skill” or “Language” is present in the competency requirements. This is because we want to take into account the technical skills related to jobs, rather that soft and transversal skills. Third, we do not include vacancies that exhibit a duration (i.e. the number of days that the vacancy remains open to applicants) of 120 days or more. This is due to the nature of the Lightcast data. In many cases, it is not possible for Lightcast to determine the expiration date of a job vacancy. Where expiration dates are not available, Lightcast automatically assigns a duration of 120 days since the posting was published. This aspect of the data means that it is not possible to distinguish between 1) vacancies that are genuinely posted for 120 days and 2) vacancies where no expiration date is available. We therefore decided to exclude vacancies with durations of 120 days or more to ensure accurate measurement of vacancy durations.[5]

3. Results

3.1 EU incidence of skill shortages across ISCO 2-digit occupation level based on the 2021 ESJS

When all seven job conditions presented in Section 2.1 hold simultaneously, a job is identified as a potential skill shortage in the 2021 European Skills and Jobs Survey. According to our methodology, the overall EU share of jobs estimated to be potential skill shortages stands at around 3.5 per cent. We want to investigate in which occupations potential skill shortages are more likely to occur. In Table 3, we present the incidence of potential skill shortages across ISCO 2-digit level occupations. The first thing that is striking is that the overall incidence of potential skill shortages is relatively low and below 3 per cent for most occupations.

Table 3: Incidence of potential skill shortages across ISCO 2-digit level occupations, EU 27 + Norway and Iceland, ESJS

ISCO code	ISCO name	%
	Managers	
11	Chief executives, senior officials and legislators	9.44%
12	Administrative and commercial managers	7.13%
13	Production and specialised services managers	6.35%
14	Hospitality, retail and other services managers	6.69%
	Professionals	
21	Science and engineering professionals	8.51%
22	Health professionals	2.01%
23	Teaching professionals	6.63%
24	Business and administration professionals	7.19%
25	ICT professionals	7.83%
26	Legal, social and cultural professionals	4.26%
	Technicians and associate professionals	
31	Science and engineering associate professionals	5.34%
32	Health associate professionals	2.70%
33	Business and administration associate professionals	4.48%

[5] Note that in our analysis we exclude armed force and agricultural occupations (Armed Forces; Skilled agricultural, forestry and fishery workers; Agricultural, forestry and fishery labourers).

34	Legal, social, cultural and related associate professionals	3.21%
35	Information and communication technicians	5.92%
	Clerical support workers	
41	General and keyboard clerks	2.40%
42	Customer services clerks	2.47%
43	Numerical and material recording clerks	2.77%
44	Other clerical support workers	2.54%
	Service and sales workers	
51	Personal service workers	0.70%
52	Sales workers	1.62%
53	Personal care workers	0.94%
54	Protective services workers	1.15%
	Craft and related trade workers	
71	Building and related trades workers, excluding electricians	2.17%
72	Metal, machinery and related trades workers	1.24%
73	Handicraft and printing workers	2.00%
74	Electrical and electronic trades workers	1.84%
75	Food processing, wood working, garment and other craft and related trades workers	2.65%
	Plant and machine operators and assemblers	
81	Stationary plant and machine operators	1.34%
82	Assemblers	0.21%
83	Drivers and mobile plant operators	0.84%
	Elementary occupations	
91	Cleaners and helpers	0.30%
93	Labourers in mining, construction, manufacturing and transport	0.93%
94	Food preparation assistants	0.25%
95	Street and related sales and service workers	0.00%
96	Refuse workers and other elementary workers	1.24%
	NA/Unidentifiable	3.09%
	EU average	3.5%

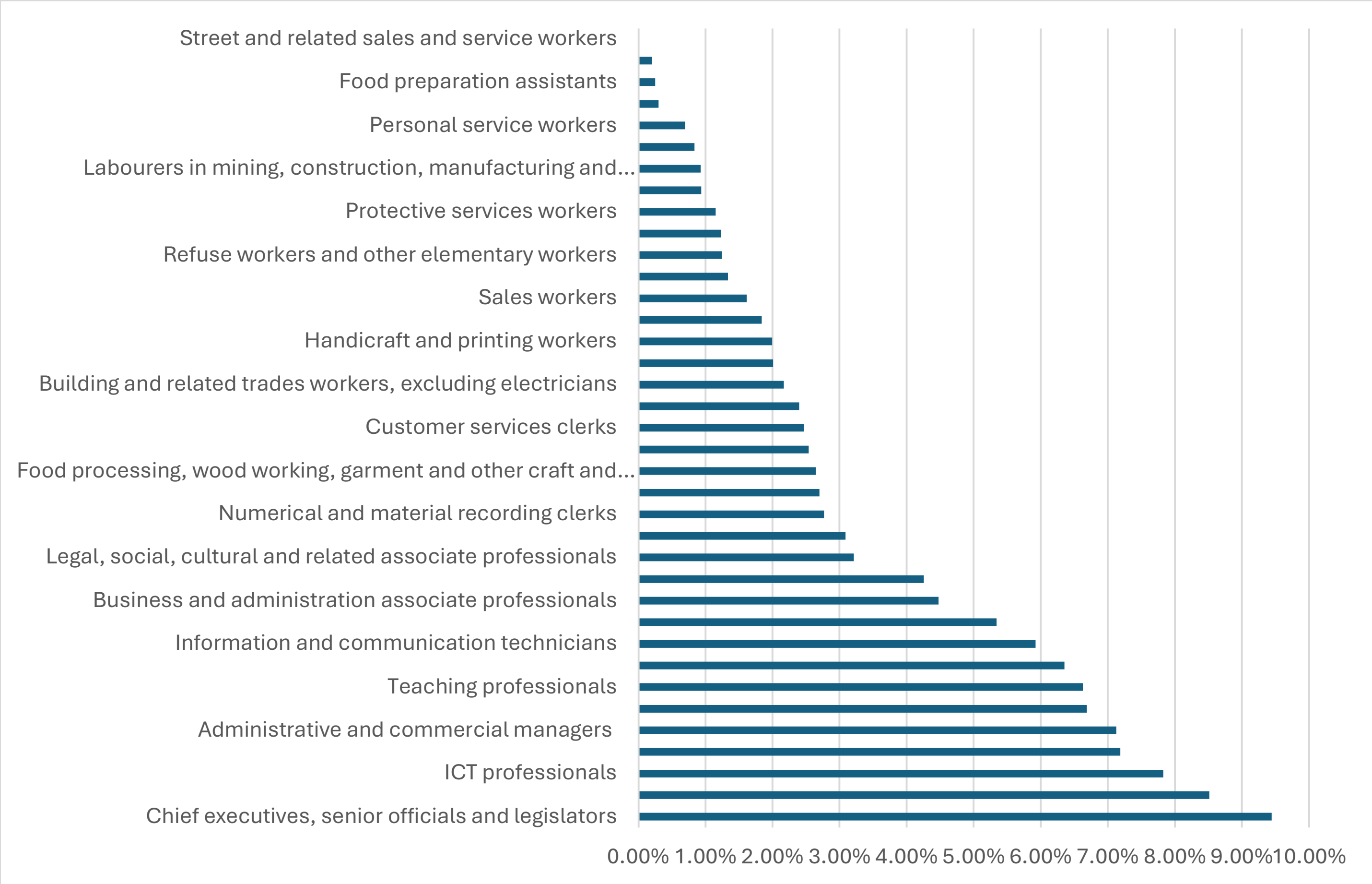
Source: 2021 European Skills and Jobs Survey (authors' elaboration).

Note: total sample is 46,212 observations. Armed Forces, Skilled agricultural, forestry and fishery workers and Agricultural, forestry and fishery labourers are excluded from the analysis.

To get a clearer idea of the occupations at highest (lowest) risk of potential skill shortages, in Figure 1 we graphically show the occupational distribution of potential skill shortages. The distribution makes sense intuitively, with many of the occupations typically thought of as having skill related hiring difficulties emerging at the top end of the distribution. The highest share of potential skill shortages appears within Chief executives, senior officials and legislators (over 9 per cent). High shares of potential skill shortages are located among professional occupations (Science and Engineering, ICT, Business and Teaching Professionals) as well as other managerial positions (Administrative and Hospitality

Managers); but potential skill shortages do exist along all the occupational distribution. As expected, elementary and service occupations have the lowest predicted incidences of potential skill shortages.

Figure 1: Potential skill shortages across ISCO 2-digit level occupations, ESJS



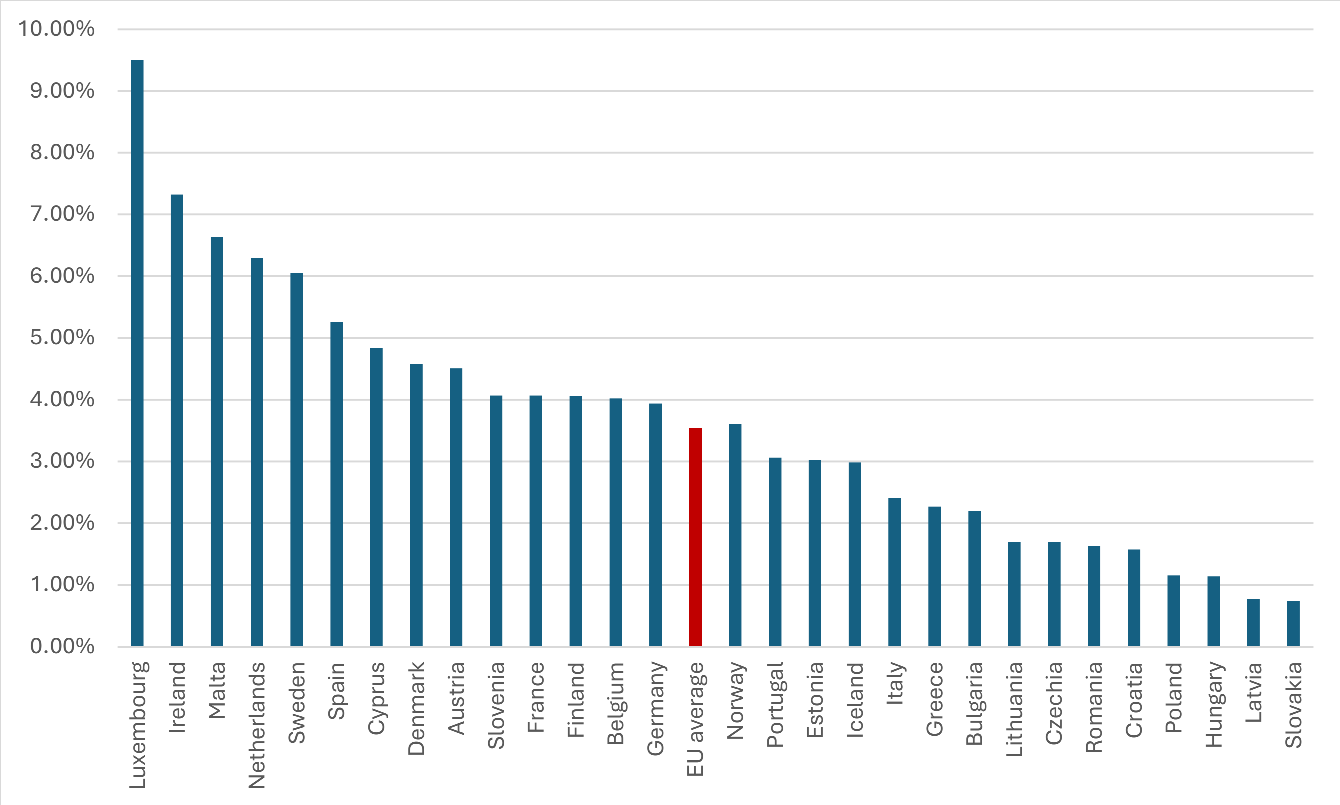
Source: 2021 European Skills and Jobs Survey (authors' elaboration).

Note: Armed Forces, Skilled agricultural, forestry and fishery workers and Agricultural, forestry and fishery labourers are excluded from the analysis.

3.2 Cross-country shares of potential skill shortages based on the 2021 ESJS

We present the cross-country distribution of potential skill shortages in Figure 2. There is substantial heterogeneity across member states, indicating that the issue of skill shortages is much more problematic in some countries than in others. Shortage rates range from over nine per cent to less than one per cent. Countries such as Luxembourg, Ireland, Malta and the Netherlands appear to have the highest share of potential skill shortages, while Slovakia, Latvia, Hungary, and Poland have the lowest.

Figure 2: Cross-country shares of potential skill shortages, ESJS



Source: 2021 European Skills and Jobs Survey (authors' elaboration).

3.3 EU incidence of skill shortages across ISCO 2-digit occupation level based on 2021 Lightcast data

When all six job posting conditions analysed in Section 2.2 hold simultaneously, a vacancy is identified as a potential skill shortage within 2021 Lightcast data. According to our methodology, the overall EU + UK share of jobs estimated to be potential skill shortages stands at around 2 percent (40,996 potential shortages out of a total 2,023,357 vacancies in 2021). We want to investigate in which occupations potential skill shortages are more likely to occur. In Table 2, we present the incidence of potential skill shortages across ISCO 2-Digit occupational categories.

Table 2: Potential Shortages, ISCO 2-Digit Occupational Categories, 2021 (Lightcast)

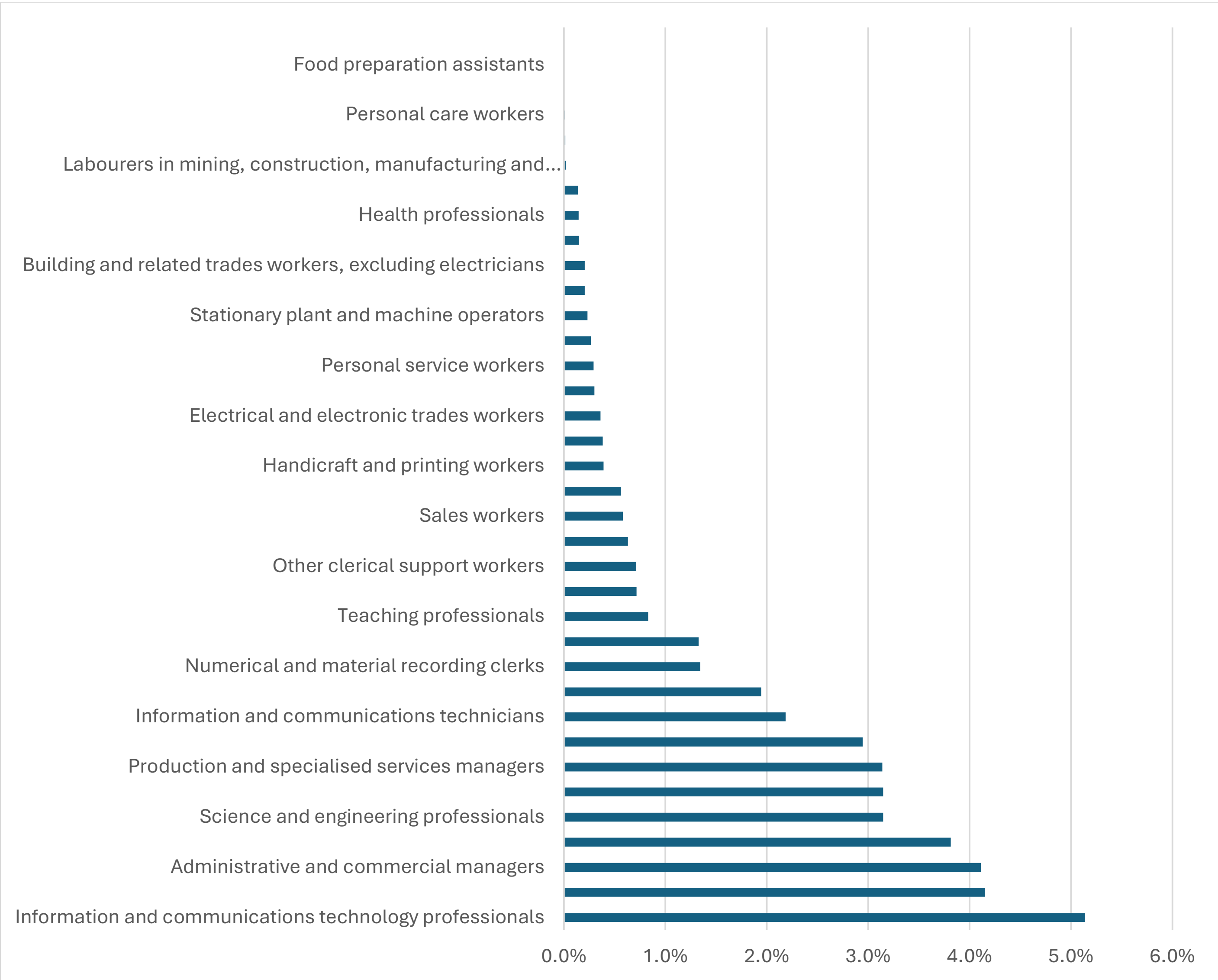
ISCO 2-Digit Category	Total Vacancies	Total Potential Shortages	Shortage Rate
Administrative and commercial managers	140,420	5,777	4.1%
Assemblers	9,043	24	0.3%
Building and related trades workers, excluding electricians	15,607	32	0.2%
Business and administration associate professionals	157,668	4,962	3.1%
Business and administration professionals	163,917	6,808	4.2%
Chief executives, senior officials and legislators	6,451	190	2.9%
Cleaners and helpers	16,576	0	0.0%
Customer services clerks	41,759	555	1.3%
Drivers and mobile plant operators	42,955	64	0.1%
Electrical and electronic trades workers	19,352	70	0.4%
Food preparation assistants	8,883	0	0.0%
Food processing, wood working, garment and other workers	20,483	42	0.2%
General and keyboard clerks	67,120	425	0.6%
Handicraft and printing workers	2,551	10	0.4%
Health associate professionals	54,448	307	0.6%
Health professionals	83,129	120	0.1%
Hospitality, retail and other services managers	28,930	1,104	3.8%
Information and communications technicians	43,973	961	2.2%
Information and communications technology professionals	174,002	8,944	5.1%
Labourers in mining, construction, manufacturing and transport	50,213	12	0.0%
Legal, social and cultural professionals	49,468	354	0.7%
Legal, social, cultural and related associate professionals	96,329	290	0.3%
Metal, machinery and related trades workers	50,086	192	0.4%
Numerical and material recording clerks	52,888	712	1.3%
Other clerical support workers	20,752	148	0.7%
Personal care workers	75,697	8	0.0%
Personal service workers	41,836	123	0.3%
Production and specialised services managers	80,548	2,530	3.1%
Protective services workers	6,386	9	0.1%
Refuse workers and other elementary workers	7,185	1	0.0%
Sales workers	66,746	388	0.6%
Science and engineering associate professionals	72,299	1,407	1.9%
Science and engineering professionals	118,416	3,728	3.1%
Stationary plant and machine operators	65,115	152	0.2%
Street and related sales and service workers	858	0	0.0%
Teaching professionals	65,046	541	0.8%
Total	**2,017,135**	**40,990**	**2.0%**

Source: 2021 Lightcast data (author's calculations).

The estimated shares are comparatively lower than ESJS estimates. While the ESJS is a representative survey of all adult employees in Europe, Lightcast data represents the number of job openings over a period of time. Given that many high-skilled roles are filled internally within organisations, it is not surprising that such positions account for a lower share of total job advertisements relative to their employment shares.

In Figure 3, we graphically show the occupational distribution of potential skill shortages and, again, these make intuitive sense. ICT professionals exhibited the highest potential skill shortage rate in 2021 (over five per cent), followed by Business and administration Professionals, and Administrative and Commercial Managers (over four per cent). Potential skill shortages are located among other professional and managerial occupations.

Figure 3: Potential skill shortages across ISCO 2-digit level occupations, Lightcast data

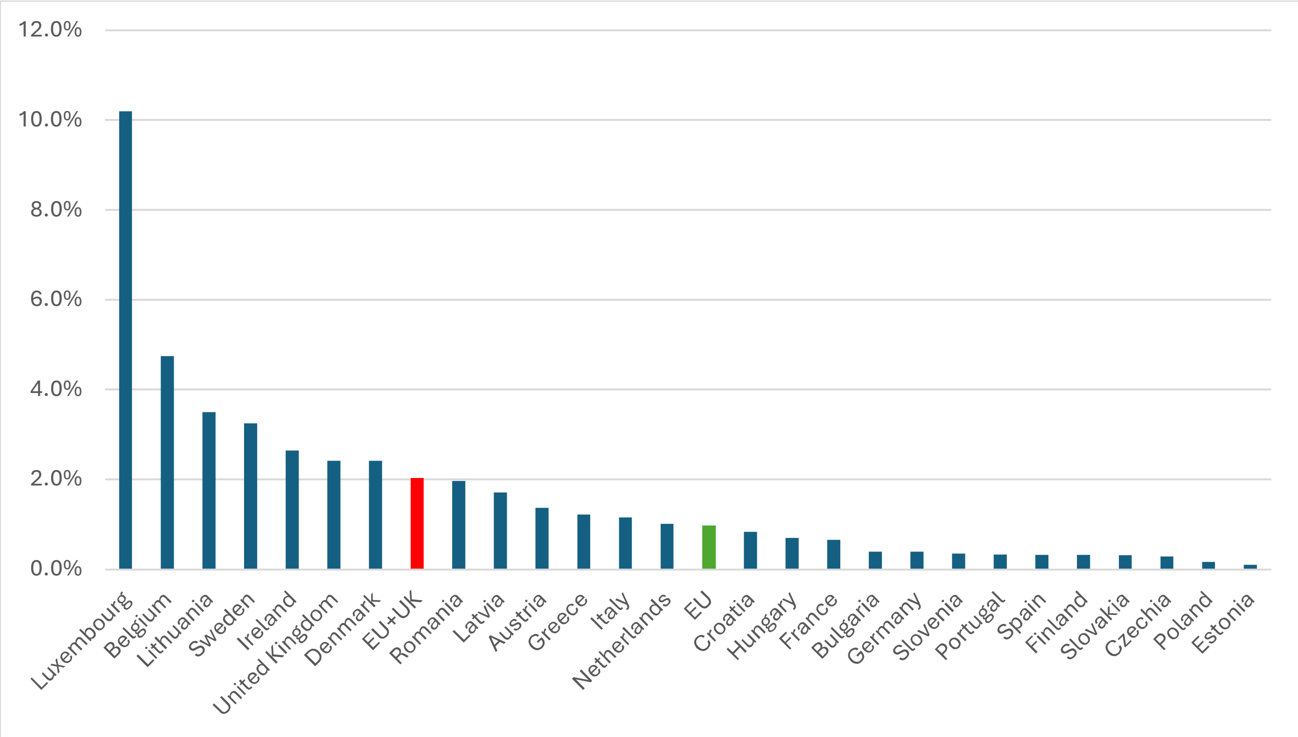


Source: 2021 Lightcast data (author's elaboration).

3.4 Cross-country shares of potential skill shortages based on 2021 Lightcast data

We also calculate the potential shortage rates for each individual country across the sample, which we graph in Figure 4 below. Luxembourg seems to display the highest shares of potential skill shortages, followed by Belgium and Lithuania; Estonia, Poland and Czechia display the lowest shared of potential skill shortages vacancies. The EU + UK average stands at 2 per cent, while if we consider only the EU 27 countries, the average is halved. Note that Cyprus and Malta are not included in the analysis due to small sample sizes.

Figure 4: Country-level rates of potential skill shortages (EU-27+UK; 2021, Lightcast)



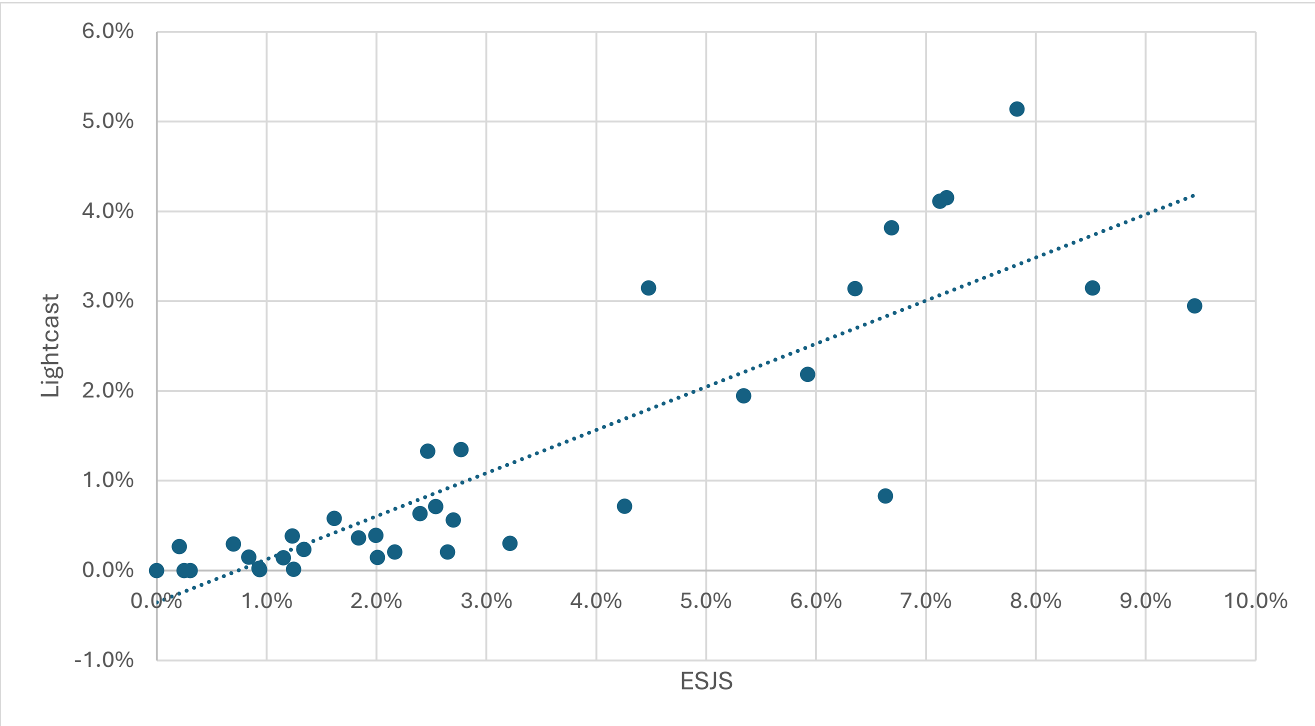
Source: 2021 Lightcast data (author's elaboration).

Note: Cyprus and Malta are not included due to small sample size.

3.5 *Benchmarking ESJS Skill Shortages estimates against Lightcast Skill Shortages estimates*

We validate our Lightcast approach against the ESJS estimates, by calculating the correlation between the potential skill shortages estimates in the two datasets. In Figure 5, we plot potential skill shortages rates in ESJS against potential skill shortages in Lightcast, at an occupational level. We observe a positive correlation (ρ = 0.87): occupations with high (low) shares of potential skill shortages in ESJS data, generally have high (low) rates of potential skill shortages in Lightcast data, although with some outliers. This is a critical finding as it confirms that our Lightcast approach predicts the vacancies that are likely to be most difficult to fill in a way that is reflective of the current distribution of competencies and skills being demanded, and utilised, in the labour market, as measured by the ESJS. When the country level estimates of skill shortage or compared with each other. The two sets of estimates are strongly positively correlated ($\rho = 0.60$) albeit the correlation is weaker than the EU level ISCO correlations.

Figure 5: Potential Skill shortages by occupation- ESJS estimates against Lightcast estimates



Source: 2021 European Skills and Jobs Survey and 2021 Lightcast data (author's elaboration).

3.5.1 Changing Skill Requirements and Potential Skill Shortages rates

As the nature of work evolves, the skills required by employers change over time. This change can happen at varying rates, depending on differing characteristics associated with specific jobs. For example, the diffusion of Artificial Intelligence (AI) may have greater implications for the required skills associated with software developers than it might have for caterers. When skill requirements change, workers are required to up- or re-skill (i.e. via education or training) in order to secure desirable employment. This training burden has the potential to be larger in occupations where skill requirements change more rapidly, as the likelihood of more new skills being required is greater, meaning that more training may be required. Given that training takes time, and skill change happens continuously, the likelihood of the existence of sufficiently skilled labour is lower in jobs where skill change happens more quickly. In other words, potential skills shortages are more likely to occur in jobs that experience more rapid changes in tasks. We therefore examine how changing skill requirements, within occupations, relate to skill shortages.

To evaluate this relationship empirically, we use measures of occupational skill change that are calculated by Redmond, Kelly and Brosnan (forthcoming). Drawing on previous work by Deming and Noray (2020), Redmond, Kelly and Brosnan (forthcoming) construct a measurement approach that is applied to EU online vacancy data. Their measure of skill change is based on Equation (1) below,

$$SkillChange_o = \sum_{s=1}^{S} \left| \frac{Skill_{s,o,2021}}{Vacancies_{o,2021}} - \frac{Skill_{s,o,2019}}{Vacancies_{o,2019}} \right| \tag{1}$$

Here, $Skill_{s,o}$ is the number of times some skill s appears in vacancies of ISCO 2-Digit occupational category o in the specified year. $Vacancies_o$ is the total number of posted vacancies for the corresponding occupational category. Therefore, we can understand $\frac{Skil_{\ s,o}}{Vacancie_{\ o}}$ to be the demand prevalence of a given skill within a given occupation. We calculate the absolute difference in demand prevalence for each skill within in each occupation between 2019 and 2021 (i.e. $\left|\frac{Skill_{s,o,2021}}{Vacancies_{o,2021}} - \frac{Skil_{\ s,o,2019}}{Vacancies_{o,2019}}\right|$).[6] This gives us an idea of the relative change in demand for each skill across time.

For example, if the skill "*SQL*" appeared 45 times out of 100 vacancies for Software Developers in 2019, but appeared 70 times out of 200 vacancies for Software Developers in 2021, this figure would be $|0.35 - 0.45| = 0.1$. Given that we examine the absolute value of

[6] We select 2019 as our base year as it represents the earliest available year in the Lightcast data for which there is a sufficient volume of data to conduct a meaningful analysis.

the difference in prevalence across years, this measure is agnostic to the direction of skill change; the measure is positively driven by both increases and decreases in the demand for skills. We calculate the absolute difference in demand prevalence for all skills in a given occupation, including those skills that were demanded in 2019 and not 2021 (i.e. “obsolete skills”), and *vice versa* (i.e. “new skills”). We then sum the difference in proportions for all skills in an occupation to get a sense of total changing skill requirements in each occupational category. Each unit of $SkillChange$ is equivalent to one skill being present in 100 per cent of vacancies in one year and 0 per cent of vacancies in the other year.

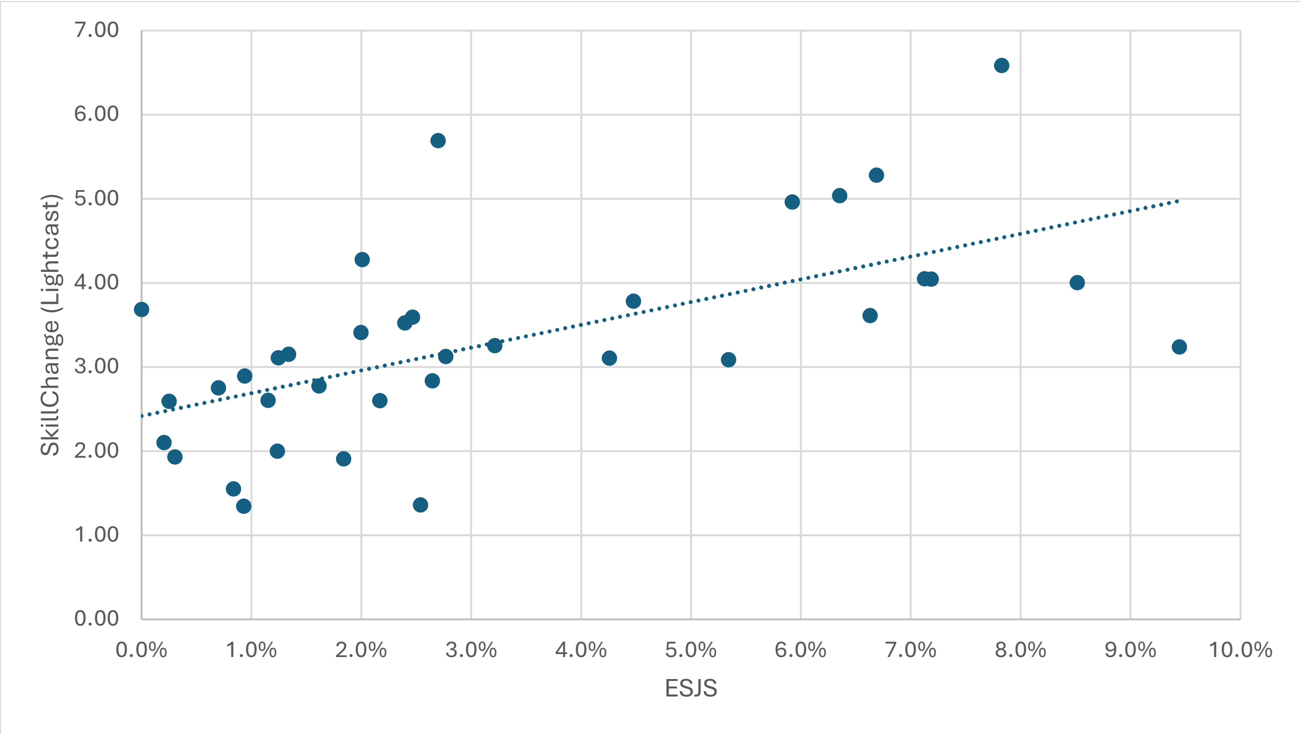
$SkillChange$ is positively dependent on both 1) the number of skills examined in a given occupation and 2) the magnitude of skill-specific change in demand prevalence over time. In other words, occupations with broader skillsets that have changed more over time will represent the highest values of $SkillChange$, while occupations with narrower skillsets and less change in demand prevalence will represent the lowest values. This measure has limitations. Under this approach, we consider a job with fifty skills that have all changed by 10 per cent between 2019 and 2021 ($SkillChange = 0.1 \times 50 = 5$) to have changed to the same extent as a job with five skills that have all changed by 100 per cent ($SkillChange = 1 \times 5 = 5$). It is arguable that the second case exhibits more skill change than the first case, as the entire skillset has been replaced over time. However, as there are only a total of five skills in this occupation ($S = 5$), $SkillChange$ is limited.

We note that Information and Communications Technology Professionals (ISCO 25), Health Associate Professionals (ISCO 22) and Hospitality, Retail and Other Services Managers (ISCO 14) exhibited the highest levels of skill change between 2019 and 2021 (see Appendix Table 1A for details). Contrastingly, Labourers in Mining, Construction, Manufacturing and Transport (ISCO 93), Other Clerical Support Workers (ISCO 44) and Drivers and Mobile Plant Operators (ISCO 83) were the three occupational categories with the lowest levels of changing skill requirements per online job markets. Broadly speaking, jobs with more of a technical focus – or at least require some basic digital competency – exhibited higher levels of skill change, while jobs with more of a manual focus (e.g. Cleaners and Helpers, Drivers and Mobile Plant Operators, Labourers), experienced lower levels of skill change over the two-year period.

We explore the association between changing skill requirements and potential skill shortages in the labour market. We graph the relationship between $SkillChange$ and the potential skill shortage rates calculated using the ESJS (Figure 6) and Lightcast (Figure 7) below, and we compute the correlation between skill shortages rates and the *SkillChange* measure.

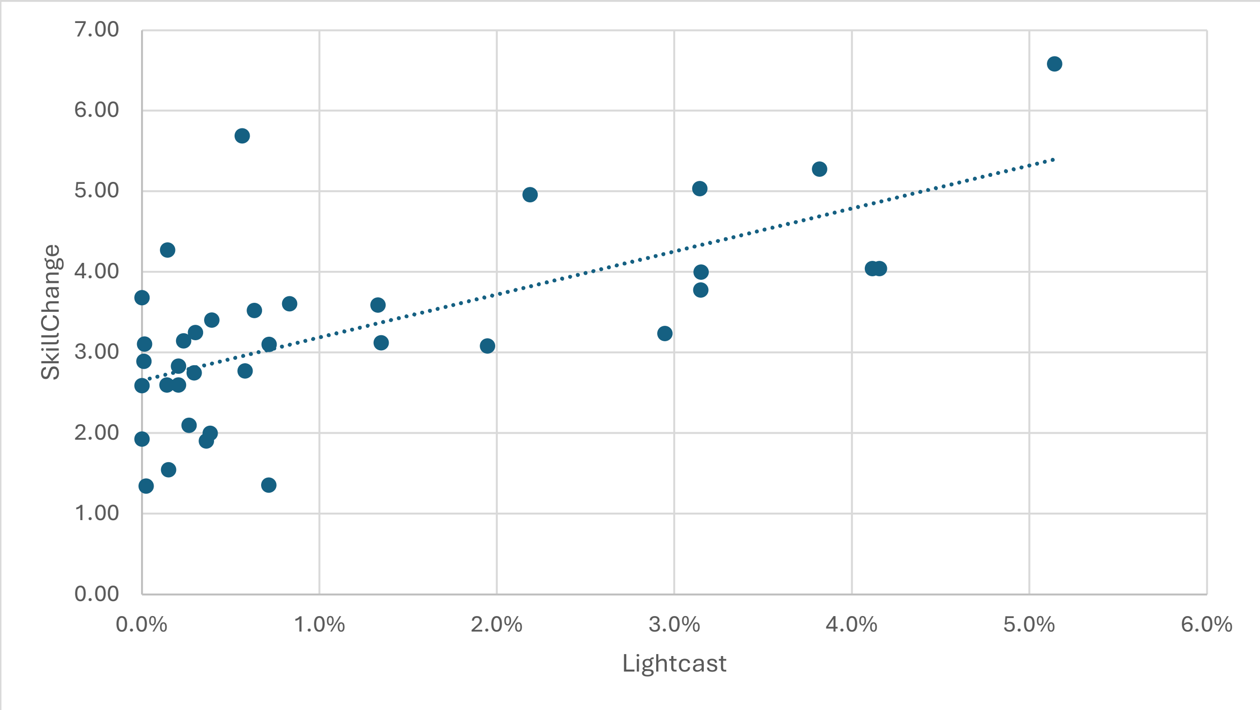
We do find that ESJS and Lightcast skill shortage rates are positively corelated with the *SkillChange* figure. This means that potential skill shortages are more likely to occur in occupations where skill requirements are changing more quickly.

Figure 6: Potential skill shortages rates (ESJS) against $SkillChange$ rates, ISCO 2-Digit Level (EU-27 + UK, 2021)



Source: 2021 European Skills and Jobs Survey and Lightcast data (author's elaboration).

Figure 7: Potential Skill Shortage Rates (Lightcast) against $SkillChange$ rates, ISCO 2-Digit Level (EU-27 + UK, 2021)



Source: Lightcast data (author's elaboration).

The correlation coefficients for the shortage rates calculated using both the ESJS and Lightcast, as well as the corresponding occupational $SkillChange$ measure, are included in Table 3 below. The correlation between Lightcast shortages rates and *SkillChange* is 0.6, while the correlation coefficient between the ESJS rate and *SkillChange* is 0.61.

Table 3: Correlation Table (Shortage Rate- Lightcast); Shortage Rate- ESJS; $SkillChange$ - Lightcast)

	Lightcast Shortage Rate	SkillChange (2019-2021)	ESJS Shortage Rate
Shortage Rate (Lightcast)	1.00		
SkillChange (2019-2021)	0.66	1.00	
Shortage Rate (ESJS)	0.87	0.61	1.00

Source: 2021 European Skills and Jobs Survey and Lightcast data (author's elaboration).

3.6 Potential skill shortages rates across ISCO 2-digit occupations using the 2022 and 2023 Lightcast data

As stated, the principal advantage of the Lightcast approach is that it can be replicated across years and countries, as new Lightcast data becomes available. As a robustness check, we next examine the incidence of potential skill shortages in later years of Lightcast data. Specifically, we identify potential skill shortages by applying the same conditions explained in Section 2.2 using job vacancy data from 2022 and 2023. It is important to assess whether potential skill shortages identified in Lightcast data in 2021 persist, increase or decrease in subsequent years. It is also important to confirm that subsequent Lightcast estimates continue to closely align with the distributions of skills and human capital being utilised within the labour market. We present the occupational distribution of skill shortage rates for 2021-2023 in Table 4 overleaf.

Generally, potential skill shortage rates are stable across time, with most occupational categories fluctuating within a band of ±1 percentage point between 2021 and 2023. Information and Communications Technology professionals, Business and Administration Professionals and Administrative and Commercial Managers display the highest share of potential skill shortages across the years, although ICT Professionals exhibited a decline of approximately two percentage points over the period of interest (from 5.1 to 3.1 per cent)

Table 4 Potential Shortages, ISCO 2-Digit Occupational Categories, 2021, 2022 and 2023 Lightcast data

ISCO 2-Digit Category	Potential Shortage Rate (2021)	Potential Shortage Rate (2022)	Potential Shortage Rate (2023)
Administrative and commercial managers	4.1%	3.2%	3.5%
Assemblers	0.3%	0.4%	0.7%
Building and related trades workers, excluding electricians	0.2%	0.3%	0.5%
Business and administration associate professionals	3.1%	2.6%	2.7%
Business and administration professionals	4.2%	3.2%	2.9%
Chief executives, senior officials and legislators	2.9%	2.5%	2.9%
Cleaners and helpers	0.0%	0.0%	0.0%
Customer services clerks	1.3%	0.9%	0.5%
Drivers and mobile plant operators	0.1%	0.1%	0.2%
Electrical and electronic trades workers	0.4%	0.4%	0.9%
Food preparation assistants	0.0%	0.0%	0.0%
Food processing, wood working, garment and other craft and related trades workers	0.2%	0.3%	0.2%
General and keyboard clerks	0.6%	0.5%	0.7%
Handicraft and printing workers	0.4%	0.3%	0.7%
Health associate professionals	0.6%	0.5%	0.7%
Health professionals	0.1%	0.2%	0.3%
Hospitality, retail and other services managers	3.8%	2.6%	2.0%
Information and communications technicians	2.2%	1.7%	2.3%
Information and communications technology professionals	5.1%	4.3%	3.1%
Labourers in mining, construction, manufacturing and transport	0.0%	0.1%	0.0%
Legal, social and cultural professionals	0.7%	0.6%	0.6%
Legal, social, cultural and related associate professionals	0.3%	0.3%	0.4%
Metal, machinery and related trades workers	0.4%	0.4%	0.7%
Numerical and material recording clerks	1.3%	1.3%	1.3%
Other clerical support workers	0.7%	1.0%	1.8%
Personal care workers	0.0%	0.0%	0.0%
Personal service workers	0.3%	0.2%	0.3%
Production and specialised services managers	3.1%	2.4%	2.6%
Protective services workers	0.1%	0.2%	0.4%
Refuse workers and other elementary workers	0.0%	0.1%	0.1%

Sales workers	0.6%	0.4%	0.7%
Science and engineering associate professionals	1.9%	1.4%	1.7%
Science and engineering professionals	3.1%	2.4%	2.4%
Stationary plant and machine operators	0.2%	0.3%	0.5%
Street and related sales and service workers	0.0%	0.1%	0.0%
Teaching professionals	0.8%	0.9%	1.2%

Source: Lightcast data (author’s elaboration).

3.6.1 2021 ESJS Skill Shortages against 2022 and 2023 Lightcast Skill Shortages

We investigate the correlation between potential skill shortage rates derived from Lightcast data in 2022 and 2023 and potential skill shortages rates calculated from the 2021 ESJS produced in previous sections. In all cases, we observe a strong positive correlation between the figures, with Lightcast / ESJS correlation coefficients being approximately the same for all years of Lightcast data (ρ =0.88 in 2022 and ρ =0.89 in 2023). This reinforces the result that occupations with high (low) shares of potential skill shortages in 2021 ESJS data, generally have high (low) rates of potential skill shortages in Lightcast data, also when considering later years of data (see Appendix Figure 1A and 2A). This robustness check confirms that sequential estimates generated using Lightcast data continue to closely align and reflect the actual distribution of skills and human capital being utilised within labour markets.

Table 5: Correlation Table (Shortage Rate- ESJS; Shortage Rate - 2021, 2022 and 2023 Lightcast data)

	ESJS, 2021	Lightcast, 2021	Lightcast, 2022	Lightcast, 2023
ESJS, 2021	1			
Lightcast, 2021	0.87	1		
Lightcast, 2022	0.87	0.99	1	
Lightcast, 2023	0.89	0.94	0.95	1

Source: 2021 European Skills and Jobs Survey and Lightcast data (author's elaboration).

4. Conclusion

While policymakers and governments are continually alert to the potential risks of skill shortages and routinely implement policies designed to combat them, there is no consensus on how to measure them. The limited literature contains a number of subjective and objective measurement approaches to skill shortages. However, each of these has their weaknesses and very few can be easily replicated over time and/or across countries due to data constraints.

The objective of this study is to produce a meaningful indicator of potential skill shortages, based on vacancy data, that can be replicated annually at both EU and member state level, while distinguishing skill from labour shortages Our approach uses the second wave of the European Skills and Jobs Survey (ESJS2) to identify within each occupation the proportion of jobs that are likely to be difficult to fill should they come to the labour market. The ESJS2, is an employee survey with detailed information on job characteristics. We use a multi-dimensional approach, by identifying several conditions that are likely to be associated with potential skill shortages. However, the ESJS2 is a periodic cross-section, and while any measure of potential skill shortage will reflect the distribution of jobs in 2021, it also has drawbacks in that (a) the flow of jobs that are advertised may not accurately mirror the stock of existing jobs, particularly, as many high skilled vacancies could be filled internally, and (b) the estimates of potential skill shortages cannot be replicated for years subsequent to 2021. In order to overcome these limitations, we attempt to replicate our measure of potential skill shortages based on the ESJS2 using job advertisement data from Lightcast, which will reflect the distribution of current vacancies and can be estimated on an annual basis at an EU and member state level. The benchmarking of an objective measurement approach to a dataset reflecting the current distribution of skills and competencies being utilised within the labour market is, in our view, a substantial advancement in the measurement of skills shortages at both a national and European level.

The results of our analysis produce a meaningful indicator that aligns to prior expectations regarding the likely occupational distribution of skill shortages. The incidences of potential skill shortage are found to be generally much lower, at around 2 per cent of all vacancies across the EU and the U.K., relative to estimates produced using other approaches. Many of the occupations typically thought of as having skill-related hiring difficulties emerge at the top end of the occupational distribution. Our robustness checks are highly encouraging as they suggest that our Lightcast based estimates closely reflect the distribution of skill and competencies being employed within the labour market, and these relationships are stable as the Lightcast estimates extend beyond 2021. Our estimates also align to the expectation that the vacancies most likely to be potential skill shortages are in in occupations within which the skill content is changing more rapidly over time.

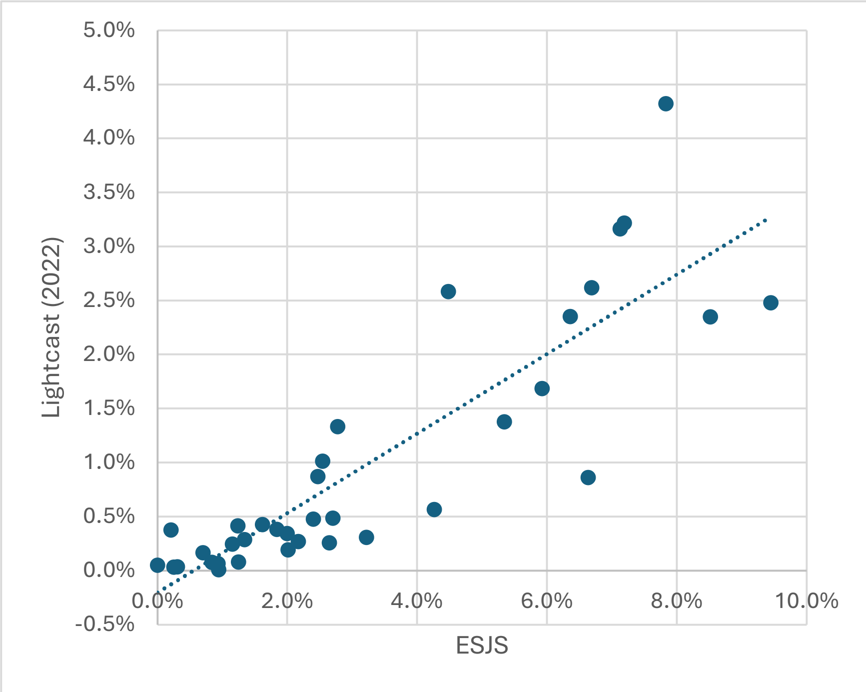
Appendix

Table 1A: $SkillChange$, ISCO 2-Digit Occupational Categories (EU-27+UK, 2019-2021)

ISCO 2-Digit Occupational Category	**$SkillChange$ (2019-2021)**
Information and communications technology professionals	6.58
Health associate professionals	5.69
Hospitality, retail and other services managers	5.28
Production and specialised services managers	5.04
Information and communications technicians	4.96
Health professionals	4.28
Administrative and commercial managers	4.05
Business and administration professionals	4.04
Science and engineering professionals	4.00
Business and administration associate professionals	3.78
Street and related sales and service workers	3.68
Teaching professionals	3.61
Customer services clerks	3.59
General and keyboard clerks	3.52
Handicraft and printing workers	3.41
Legal, social, cultural and related associate professionals	3.25
Chief executives, senior officials and legislators	3.24
Stationary plant and machine operators	3.15
Numerical and material recording clerks	3.12
Refuse workers and other elementary workers	3.11
Legal, social and cultural professionals	3.11
Science and engineering associate professionals	3.09
Personal care workers	2.89
Food processing, wood working, garment and other	2.83
Sales workers	2.78
Personal service workers	2.75
Protective services workers	2.60
Building and related trades workers, excluding electricians	2.60
Food preparation assistants	2.59
Assemblers	2.10
Metal, machinery and related trades workers	2.00
Cleaners and helpers	1.93
Electrical and electronic trades workers	1.91
Drivers and mobile plant operators	1.55
Other clerical support workers	1.36
Labourers in mining, construction, manufacturing and transport	1.35

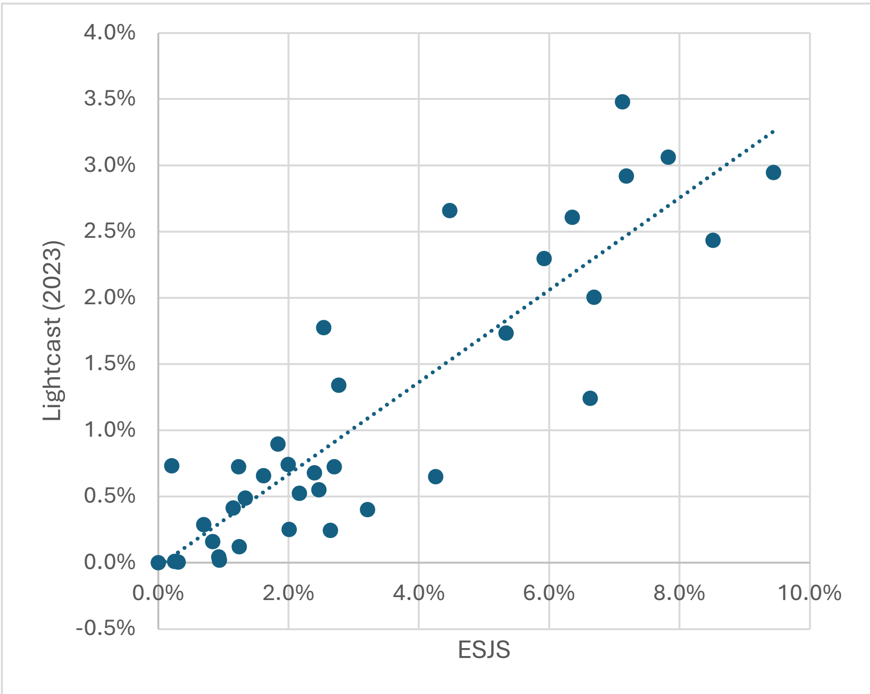
Source: Lightcast data (Author's Calculations)

Figure 1A: Potential Skill shortages by occupation- 2021 ESJS estimates against 2022 Lightcast estimates



Source: 2021 European Skills and Jobs Survey and 2022 Lightcast data (author's elaboration).

Figure 2A: Potential Skill shortages by occupation- 2021 ESJS estimates against 2023 Lightcast estimates



Source: 2021 European Skills and Jobs Survey and 2023 Lightcast data (author's elaboration).

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