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Skills Mismatch, Automation, and Training: Evidence from 17 European Countries Using Survey Data and Online Job Ads*

KEY MESSAGES

- **Linking survey data and online job ads offers new insights into skills gaps in the EU**
- **Matching labor market needs and skill supply remains a Europe-wide challenge**
- **Manual workers have skill supply shortages, cognitive workers have skill supply surpluses**
- **Workers at higher risk of automation experience higher skill shortages, potentially because their job tasks are changing more rapidly**
- **On-the-job training might be a potential measure to meet future skills needs**

Labor markets face challenges due to globalization, structural transformation, and advancing technological change. This can lead to skills gaps and skills mismatch between firms' skill demand and employees' skill supply, which can go in two directions: workers having a skill surplus, where skill supply exceeds demand, or workers experiencing skill shortage, where firms' skill demand is greater than the skills workers actually possess. In light of this, the EU's Agenda for New Skills and Jobs (European Commission 2020) states that creating a more skilled workforce "is a considerable challenge given the rapidly-changing skills needed, and the persistent skills mismatches in the EU labor market." In this report, the Commission also "established the anticipation and matching of labor market and skills needs as a top priority for the EU."

However, empirical evidence on the prevalence of skills mismatch between the skills requested by employers and the skills provided by employees across Europe is scarce. We contribute to the understanding of skills mismatch in the EU by presenting novel evidence on skills gaps across countries, occupations, and skill domains using innovative job ad data and survey data for 16 EU countries and the UK.[1] In particular, we leverage two different data sources: online job vacancy data on skills requested by employers and survey data on skills supplied by workers. We document four key findings: first, skill gaps in the European Union exist, but the extent and direction vary across occupation types: workers in cognitive intensive occupations provide more skills than are demanded (skill surplus), whereas workers in manual intensive occupations face higher skill demand compared to the skills they have (skill shortage). Second, this pattern is consistent across almost all 17 countries that are part of our analysis. This suggests that overall patterns of skills mismatch do not reflect country-specific factors but are rather a European-wide phenomenon. Delving deeper into different skill domains (i.e., digital, numeracy, literacy, and social skills), we document similar skills gaps for different occupation types. Thus, the observed skills gaps are not driven by a lack of specific skill domains such as digital skills. Finally, we investigate potential mechanisms – i.e., an occupation's automation probability and workers' propensity to participate in on-the-job training – that might underlie the observed patterns of skills mismatch.

LINKING SURVEY DATA AND ONLINE JOB ADS OFFERS NEW INSIGHTS INTO SKILLS GAPS IN THE EU

We propose a novel measure of the gap between the skills demanded by employers and the skills supplied by workers. On the demand side, we rely on online job vacancies (OJV) data from the European Center for the Development of Vocational Training (CEDEFOP), collected in 2019, to capture skills de-

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[1] These countries are Belgium, Cyprus, Czech Republic, Denmark, France, Germany, Greece, Ireland, Italy, Lithuania, Netherlands, Poland, Slovakia, Slovenia, Spain, Sweden, and the UK.

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manded by employers.[2] On the supply side, we use survey data from the Programme for International Assessment of Adult Competencies (PIAAC). PIAAC comprises representative samples of working-age individuals from 17 European countries; data were collected in 2012 and 2014, respectively. Here, respondents working in different occupations were asked about their skill use at work in different skill domains. Among others, these skill domains cover digital, numeracy, literacy, and social skills.

Nonetheless, the two data sources are not directly linked at the skill level. To combine the data, we developed an AI-driven tool using word embeddings that maps skills mentioned in OJV to the skills elicited in PIAAC items. Our final mapping links, for instance, the skills "Coaching young people" and "Instruct others" stated in OJV to the PIAAC skill item "Teaching people."

COMPARING SKILL DEMAND AND SKILL SUPPLY

To quantify the gap between skills on the demand side from OJV data and the skills provided on the supply side in PIAAC, we have developed a measure of skills mismatch based on the importance of each skill for each occupation. Specifically, our measure of skills gap is based on differences in the revealed comparative advantage (RCA) of each skill in each occupation between the OJVs and PIAAC. Intuitively, the RCA of a skill is a measure of its prevalence or frequency in each occupation relative to the frequency in all other occupations. For further details on this measure, see the Technical Box.

First, we calculate the RCA of each skill for each occupation in both OJV and PIAAC. Next, for each skill, we compute the rank of the RCA across all occupations on both the demand and supply side. For instance, if the RCA of "Teaching people" is ranked at the top five percent for teaching professionals on the supply side, this means that teachers have a high RCA in this skill among all occupations.

Thus, differences in the RCA ranks of skills between demand and supply reflect potential mismatches in skill relevance. We define the gap in skill ranks as the percentile rank on the demand side minus the percentile rank on the supply side. Thus, a positive value indicates that the RCA of the demand for a skill is larger than the RCA of the skill supplied in a particular occupation. We refer to this case as skill shortage. For instance, the importance of "Reading financial statements" is at the 61st percentile on the demand side for teaching professionals, while it is at the 43rd percentile on the supply side, resulting in a positive skill gap of 18 percentile ranks. Thus, teaching professionals have a skill supply shortage for the skill of "Reading financial statements." Conversely, a negative skill gap indicates a skill surplus. For the skill "Reading e-mails", teaching professionals have a skill surplus: the importance of this skill is at the 68th percentile on the demand side and at the 82nd percentile on the supply side, resulting in a negative skill gap of -14 percentile ranks.

MATCHING LABOR MARKET NEEDS AND SKILL SUPPLY REMAINS A CHALLENGE

The literature often distinguishes between four occupation types: manual routine, manual non-routine,

[2] For most countries, PIAAC is only available for 2012. However, the earliest job vacancy data from CEDEFOP stem from 2019. To remedy the issue of temporal misalignment between PIAAC and OJV, we use the skill change in the US, for which the PIAAC survey was conducted in 2012 and 2017, to project skill changes for all other countries. Assuming that changes in the occupational skill content in the US represent changes at the technological frontier (e.g., Caunedo et al. 2021), these changes can be used to project an upper bound of how skills have evolved in other PIAAC countries.

TECHNICAL BOX: RCA WITH ONLINE JOB ADVERTISEMENTS AND PIAAC

The concept of revealed comparative advantage (RCA) was developed in international trade economics to represent countries' export specialization (e.g., Balassa 1965). The measure, when applied in the context of occupations and skills, can be understood as the relevance of a skill for an occupation, relative to all other occupations. We follow the approach developed by Alabdulkareem et al. (2018), which calculates the RCA using the O*NET dictionary of occupations and skills; O*NET surveys a sample of workers in the US to assess the relevance of a skill for each occupation. We calculate it using online job ads as proposed in Giabelli et al. (2022). The relevance is computed as the frequency of a skill in the job ads for a specific occupation, relative to the skill's frequency in job ads in all other occupations. Analogously, the RCA of a skill in PIAAC is computed as the frequency of skill use among survey respondents in a given occupation, relative to survey respondents in all other occupations.

cognitive non-routine, and cognitive routine occupations (Autor et al. 2003). These occupations differ in the tasks workers need to perform on the job. For instance, food preparation assistants perform predominantly manual, routine-intensive tasks, such as manual assembling and quality checks. On the other hand, teaching professionals perform predominantly cognitive and non-routine tasks, such as using advanced mathematics and teaching people. At the same time, structural transformation and technological change have different impacts on different types of tasks. Automation technologies have particularly rendered codifiable routine and manual tasks susceptible to substitution by automation. As the task composition and thus the skill requirements of different occupations are affected differently by technological change, this also renders occupations more or less susceptible to changing skills demands and skills mismatch, which we also refer to as skills gaps.

Figure 1 depicts the average skills gap between demand and supply by occupation across all countries in our sample. There is an intriguing difference between manual and cognitive workers in the average skill gap. While cognitive non-routine and cognitive routine workers have a skill supply surplus on average (negative skill gap), manual non-routine and manual routine workers exhibit skill supply shortage (positive skill gap). For instance, business administration professionals exhibit the highest skill surplus: they provide more skills than are required in respective job ads. For this occupation, the relevance of the skills demanded ranks below the skills provided by business administration professionals by 48 percentiles. Cleaners and helpers, on the other hand, show the most pronounced skill shortage: The skill requirements in this occupation exceed their skill supply by 55 percentiles. Health professionals, Electrical workers, ICT professionals, and ICT technicians feature the narrowest skill gaps. Below, we discuss potential mechanisms underlying these patterns across occupations, such as the risk of automation and on-the-job training of employees.

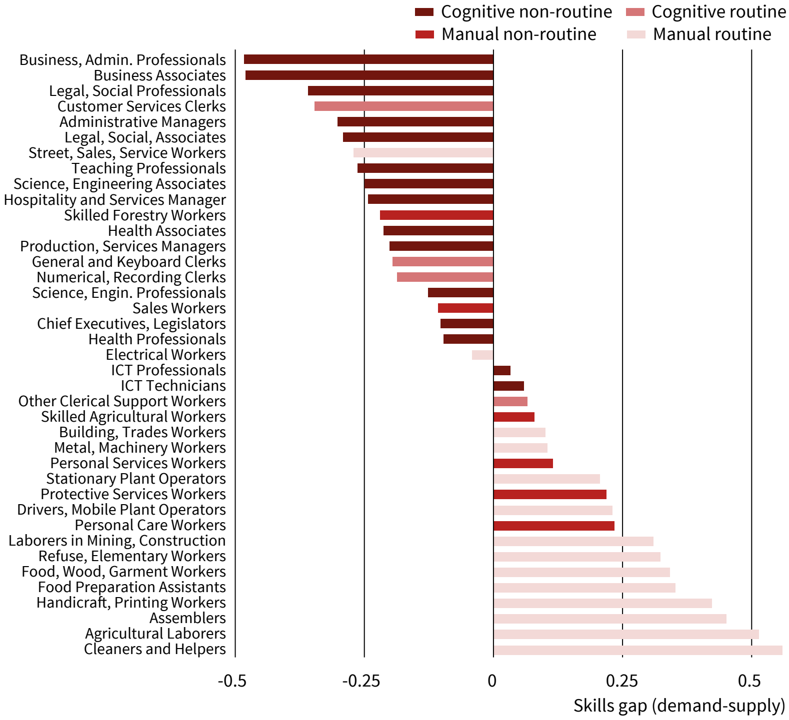
SKILLS GAPS ARE A EUROPE-WIDE CHALLENGE

This pattern of skills mismatch is strikingly consistent across Europe. Figure 2 plots the difference in skills gaps by occupation types for different European countries. Skills gaps by countries for cognitive non-routine, cognitive routine, manual non-routine, and manual routine occupational types are presented in panels 1, 2, 3, and 4, respectively. The dotted line represents the average skills gap over all countries within an occupation type.

We can clearly see that the skill shortage for workers in manual-intensive occupations and the skill surplus for those in cognitive-intensive occupations is persistent across EU countries. For almost all countries, cognitive workers show a skill supply surplus, while manual workers have a skill supply shortage on average. The only exceptions are Sweden for manual non-routine workers and France for cognitive routine and manual non-routine workers.

Figure 1

Skills Gaps by Occupation



Note: Pooled for 17 European countries.
Source: CEDEFOP; PIAAC.
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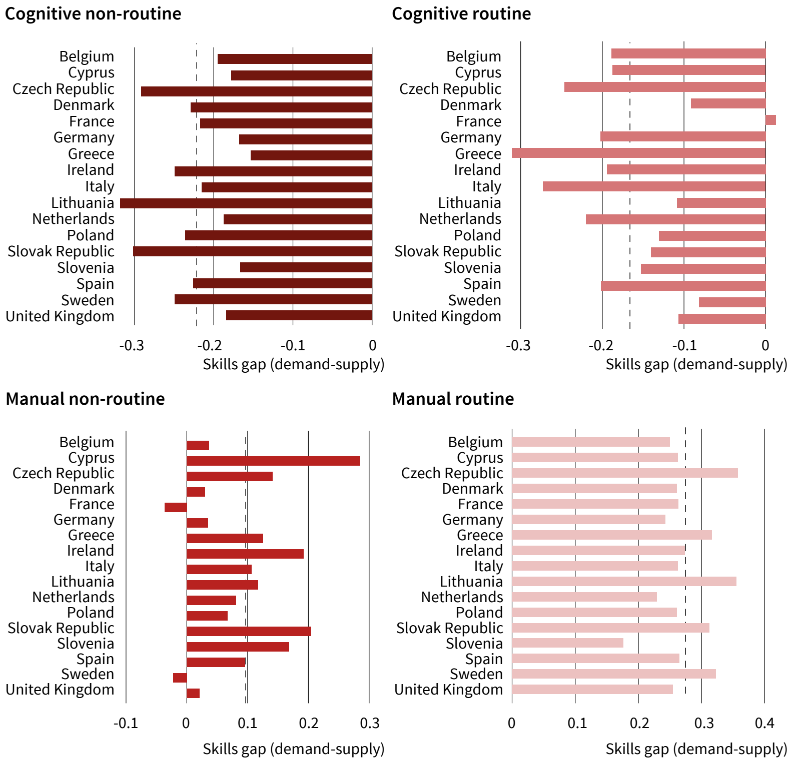
Figure 2

Skills Gaps by Country and Occupation Type



Note: Skills gap by occupation type – cognitive non-routine, cognitive routine, manual non-routine, and manual routine – are shown for 17 European countries. The dotted line shows the occupation-type-specific mean over all countries.
Source: CEDEFOP; PIAAC.
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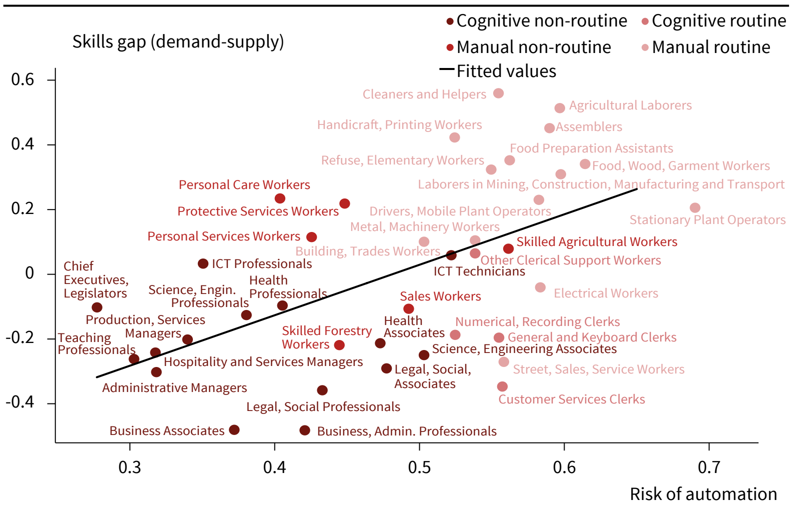
Figure 3

Skill Gaps by Skill Domain and Occupation Type

Figure 4

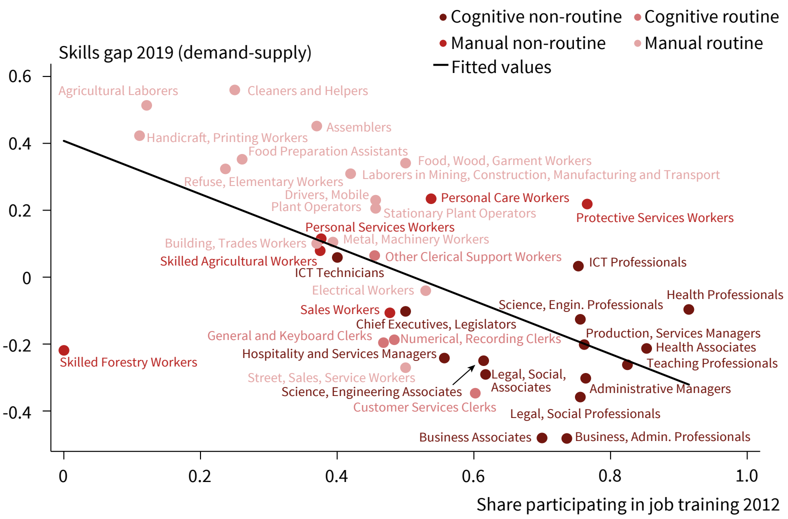
Automation Risk and Skill Gaps



Note: Correlation between automation risk and the skills gap, pooled for 17 European countries. Our measure of automation risk stems from Nedelkoska and Quintini (2018), who constructed the automation probability for all occupations and countries in our sample using PIAAC data.
Source: CEDEFOP; PIAAC.

Figure 5

Job Training and Skill Gaps



Note: Correlation between on-the-job training (measured in 2012) and the skills gap (measured in 2019), pooled for 17 European countries.
Source: CEDEFOP; PIAAC.

SKILL GAPS ARE SIMILAR ACROSS ALL SKILLS DOMAINS

One potential driver of the positive skills gaps of manual workers could be a supply shortage of specific in-demand skills that have gained importance in recent years, such as digital skills. To investigate this, we separate the skills gap for each occupation group by different domains (digital, numeracy, literacy, and social skills) in Figure 3. However, we find similar skills gaps across all skill domains for our four occupation types: cognitive workers show skill a supply surplus on average, while manual workers exhibit a shortage on average. Further, the supply shortage across all skill domains is largest for manual routine workers, while the surplus is highest among cognitive non-routine workers.

WORKERS AT HIGHER RISK OF AUTOMATION FACE HIGHER SKILL SHORTAGE

Next, we explore potential mechanisms that might underlie our previous results. A large body of literature suggests that routine occupations are particularly exposed to automation risks (e.g., Frey and Osborne 2013; Arntz et al. 2016; Nedelkoska and Quintini 2018). Thus, occupations with higher susceptibility to automation are at larger risk of their tasks being replaced by robots and automation technologies. Accordingly, the skills requirements for these occupations change more rapidly (e.g., Acemoglu and Restrepo 2019; Deming and Noray 2020), and occupations with a higher risk of automation should face larger skills gaps. Our data provide suggestive evidence for this.

Figure 4 depicts the relationship between the skills gap and the risk of automation across occupations. Our measure of automation risk stems from Nedelkoska and Quintini (2018), who constructed the probability of being automated for all occupations and countries in our sample using PIAAC data. For instance, teaching professionals have a probability of 31 percent that their occupation is being substituted by automation, while it is 68 percent for food preparation assistants.

Figure 4 shows a positive relationship between the risk of automation and the average skill shortage of occupations: a higher risk of automation is associated with higher skills gaps (demand-supply). Thus, occupations more exposed to the risk of automation, such as food preparation assistants and plant operators, exhibit skill supply shortages. This is consistent with the notion that as automation technologies become able to perform existing tasks, skill demand for these occupations changes more rapidly and workers face larger challenges to meet these new skill demands. At the same time, occupations at lower risk of automation have skill supply surpluses, indicating that they provide more skills than currently required from employers.

ON-THE-JOB TRAINING AS A POTENTIAL MEASURE TO MEET FUTURE SKILLS NEEDS

We have shown that workers in manual occupations are more exposed to automation risk and face larger skill shortages, which potentially stem from more rapid changes in skills requirements due to the automation of existing tasks.

One measure to mitigate the adverse ramifications of technological change on skills gaps is training to re-educate employees so as to prepare them for changing skill demands. Indeed, Figure 5 shows that workers in occupations with a higher share of workers participating in training in the PIAAC data (measured in 2012) are less likely to exhibit skill shortages in 2019. We use the training intensity in the year 2012, as it is likely that the degree of skills mismatch of employees in an occupation in 2019 depends on the participation in, or missing out on, training in the past. Thus, a potential explanation for this could be that workers in occupations with more training were better at anticipating skills demand changes and investing in on-the-job training to stay on the frontier of what is demanded in their respective job. Conversely, there is a skill supply shortage in 2019 for occupations that showed low rates of training in 2012. At the same time, occupations with lower training intensities in 2012 are also those more exposed to automation risks, such as manual occupations like agricultural laborers and food preparation assistants. This suggests that workers who did not invest in job training were not prepared for changing skill requirements and thus show more pronounced skill shortages.[3]

POLICY CONCLUSIONS

This article addressed two questions of high relevance for European Union policymakers: (1) how prevalent is skills mismatch in Europe?, and (2) what are the drivers of these skills gaps and how can workers better prepare for the skill demand of employers? Drawing on innovative online job ad data and survey data for 17 European countries, we created novel measures of skills mismatch. We documented that manual workers face skill shortages, while cognitive workers exhibit skill surpluses. This basic pattern holds across all the 16 EU countries, plus the UK, that we analyzed in this report. We further found that this Europe-wide pattern is not driven by single occupations or increased demand for certain skill domains, such as digital skills, but is strikingly consistent across all occupations and skill domains.

Are technological change or differences in training provision important driving or mitigating factors for these patterns? Figure 4 shows that technological change (proxied by an occupation's automation probability) is more prevalent in manual routine and manual non-routine occupations compared to their cognitive counterparts. Thus, our results suggest that job-specific knowledge of manual workers becomes obsolete more rapidly: the skills that were previously essential for a manual job lose relevance, which leads to skill shortages. In comparison, the skill content of cognitive non-routine and cognitive routine occupations is less exposed to automation. However, cognitive workers might be better able to anticipate the changes in skill content due to automation and invest in on-the-job training early on to guarantee their employability. This, in turn, leads to a skill surplus for these workers. Labor market policies need to ensure that manual workers are not left behind when it comes to training provision.

The EU has given top priority to understanding and mitigating skills gaps (European Commission 2020). Our descriptive evidence points to the fact that skills gaps are prevalent in the European Union and are accompanied by skill depreciation and lower adaptability to technological change. This has adverse impacts on workers in terms of earnings and job satisfaction, but also for firm productivity. Anticipation of future skills needs and providing the opportunity for on-the-job training are thus of fundamental importance for European countries to increase productivity, job satisfaction, and competitiveness of both employers and employees.

[3] See also Falck et al. (2022), who show a positive association between training participation and digital skills for elderly workers.

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