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Power to Skills- Mapping Regional Skill Gaps

Assessing the hydrogen skill gap in German regions with a task-based approach

A working paper from the research project "Wasserstoffatlas Deutschland"

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Executive Summary

The profound structural changes associated with rapid technological progress and the green transition will have a major impact on the labour markets around the world. A lively debate is emphasising the central role that workers' skills must play in finding the best policy solutions. (Local) policy makers need to be able to assess well in advance how workers with a given set of skills can adapt to the emergence of new tasks, such as those needed in the green economy, and the disappearance of old ones, such as those needed in automatable occupations.

The present study proposes a task-based approach to measure regional skill gaps. The approach builds on the combination of a detailed dictionary of occupations and skills (ESCO) and employment data at the (sector-)occupation level. Based on the skill set of each occupation, a matrix of bilateral skill-distances is defined. Then, given a set of "target occupations," it is possible to assess the gap between the current or projected skill-sets of the workers in an entity of interest (e.g. region or industry) and the target sets needed.

The approach is applied to the case of the hydrogen skill gap in Germany to provide a rough estimate of the preparedness of each NUTS3 region in terms of the skills of its labour force. The analysis reveals the existence of clear geographical clusters. In particular, the most prepared regions are located in areas with a strong manufacturing tradition, particularly in the Ruhr area in the north-west and in the automotive industry in the south-west. In contrast, the least prepared regions are located in the centre and centre-west, in rural areas. The advantage of the most prepared regions is driven by their ability to easily fill the target quotas for technical middle and high-skilled occupations. These dynamics explain the regional clusters, as the manufacturing regions have more abundancy of workers with such skill profiles.

The approach can have multiple other applications. For example, it can be applied to the de-commissioning of coal mines, to estimate how many brown-jobs could plausibly migrate to renewable and other (non-fossil) energy sources.

Table of Contents

List of Figures

List of tables

List of Abbreviations

BIBB	Bundesinstitut für Berufsbildung.
CAPEX	Capital Expenditure.
CEDEFOP	European Centre for the Development of Vocational Training.
ESCO	"European Skills, Competences, Qualifications and Occupations" is the European multilingual classification of skills, competences, qualifications and occupations.
GDP	Gross Domestic Product.
ILO	International Labour Organization.
ISCO-08	International Standard Classification of Occupations, 2008 edition.
MW	Megawatt.
NACE	Statistical classification of economic activities adopted by the European Union. The term NACE is derived from the French title: *Nomenclature statistique des Activités économiques dans la Communauté Européenne*.
NUTS3	Nomenclature of Territorial Units for Statistics adopted by the European Union. The term NUTS is derived from the French title: *Nomenclature des Unités Territoriales Statistiques*.
OECD	Organization for Economic Co-operation and Development.
O*NET	Occupational Information Network. US-based Occupation dictionary.
OPEX	Operating Expenditure.
P2X	Power-to-X (P2X) is the generic term for the conversion of electricity into something else, in this report green hydrogen.
PIAAC	Programme for the International Assessment of Adult Competencies.
RES	Renewable Energy Sector.
WSG	Weighted Skill Gap.

1. Introduction

Skill mismatch is defined as a "discrepancy between the skills that are sought by employers and the skills that are possessed by individuals" (ILO, 2020). This discrepancy can manifest in various forms, which may also co-exist (Brunello & Wruuck, 2021). Indeed, this rather broad definition encompasses many forms of labour market frictions such as over or under skilling (vertical mismatches), horizontal mismatches, skill gaps, and skill shortages (McGuinness et al., 2018).[1]

No matter what form they take, skill mismatches tend to be troublesome. At the worker level, there are serious wage penalties, especially for overqualification, which ultimately affect both job and life satisfaction (Guvenen et al., 2020; Liu et al., 2016; Quintini, 2011). In addition, skill misalignment reduce the chances of landing a job altogether (Cords & Prettner, 2022; Kudlyak & Wolcott, 2019). For firms, skill gaps and shortages have negative consequences for productivity and competitiveness, affecting their ability to introduce new products, services or technologies (Kampelmann & Rycx, 2012; Mahy et al., 2015). In addition, skill mismatches lead to higher employee turnover and suboptimal work organization (Béduwé & Giret, 2011; Bender & Heywood, 2011), eventually causing the loss of profits and markets (Morris et al., 2020; Müge Adalet McGowan & Dan Andrews, 2015). For countries and regions, skill mismatches can result in higher levels of structural unemployment, and affect competitiveness and attractiveness to investors, meaning lost opportunities on the path to productive transformation (European Investment Bank, 2023; Restrepo, 2015; Şahin et al., 2014).

While skill mismatches have always existed, the issue has recently become more pronounced. In particular, skill mismatches are being exacerbated by megatrends (Brunello & Wruuck, 2021; OECD, 2017, 2019; Vandeplas & Thum-Thysen, 2019). The European Commission identifies 14 global megatrends defined as "long-term driving forces that are observable now and will most likely have a global impact" (European Commission, 2024b). Several of these trends have the potential to exacerbate skill mismatches. On the demand side, the increasing participation of women in the labour

[1] From the workers' perspective, the focus is often on vertical and horizontal mismatches. Vertical mismatches refer to the gap between a worker's level of formal education and the job's requirements, while horizontal mismatches capture the dissonance between a worker's field of specialization and the job's requirements (ILO, 2014). Horizontal skill mismatches are often related to skill obsolescence, which occurs when the skills previously used in a job are no longer needed, for example due to the introduction of new technologies or changes in production processes to meet stricter environmental regulations. From the firms' side, the attention is on skill gaps and skill shortages. Skill gaps occur when employers believe workers lack the competencies needed for their current roles, while skill shortages arise when employers cannot fill key vacancies due to a lack of qualified candidates (ILO, 2014).

force, demographic changes, and migration patterns all contribute to shifts in the availability and distribution of skills (Addison et al., 2020; Poot & Stillman, 2016; Vera-Toscano & Meroni, 2021). On the supply side, the rise of automation and artificial intelligence, along with the green transition, creates new demands for specific skill sets while making others obsolete (Cedefop, 2018; European Commission, 2023).

Correcting skill mismatches requires a long time. Therefore (local) policy makers need to be able to assess well in advance how workers with a given set of skills can adapt to the emergence of new tasks and the disappearance of old ones (Bechichi et al., 2018). For instance, while the net employment effect of the ambitious climate change mitigation packages adopted by OECD countries to reduce greenhouse gas emissions is projected to be modest, significant shifts are expected across industries, occupations, and regions (OECD, 2024). From the supply side perspective, policymakers need to evaluate where displaced workers from high-emission sectors can be re-employed, considering their skill sets. From the demand side, they must determine how readily workers necessary for more sustainable production processes can be sourced.

However, measuring potential skill mismatches is challenging. Due to a lack of data, many studies focus on vertical skill mismatches, rely on subjective measures from surveys, or develop measures based on skill requirements in the US labour market (Guvenen et al., 2020; McGuinness et al., 2018; Neffke et al., 2024). The present study proposes an approach combining detailed employment data and a rich European dictionary of occupations (ESCO) to measure horizontal skill mismatches in Europe. Given a set of target occupations, the approach allows to assess the gap between the current or projected skill set of workers in a specific entity, such as a region or industry, and the target skill sets. Furthermore, it can identify which skills are scarce and which are more readily available.

The method is applied to assess the regional skill mismatch for Hydrogen in Germany. Hydrogen has been at the centre of a debate about its potential to help extend the green transition to sectors that cannot be easily electrified (Kovač et al., 2021). Indeed, Germany aims to achieve a capacity of 10 GW by 2030 (Bundesregierung, 2024). Yet, deciding where to invest in the construction of electrolysers is not trivial. In fact, the optimal location for electrolysers depends on three critical factors: the region's specific needs, its potential for renewable energy generation, and the availability of workers with the required skill sets. While the first two factors can be assessed using relatively well-established methodologies, it is less clear how to evaluate the availability of the required skills. The approach described in the present study could help addressing this issue. Note that, while the more accurate term for the skill misalignment measured in the study is probably “horizontal skill mismatch”, from the worker’s perspective, or “skill shortage”, from the employer’s side, the term “skill gap” is used in the

rest of the report because it is more widely recognized by the general public and is commonly used as a synonym for skill mismatch outside this specific literature.

The rest of the report is organised as follows. Section 2 provides a brief overview on the most common empirical approaches to measuring skill mismatches. Section 3 describes the data and approach used in the study, while Section 4 presents the results. Section 5 concludes.

2. Measuring skill gaps: the task-content of occupations

In empirical studies the term "skill" is normally used in two ways: (i) level of formal education; (ii) specific set of abilities needed to perform different tasks. When using the first meaning, generally someone "high-skilled" is simply someone with a university degree, someone "middle-skilled" is someone with a professional or high-school degree, and those below are "low-skilled". Measuring the skills in the second sense, namely the "specific set of abilities needed to perform different tasks" is more complicated. One way to do this is through dedicated surveys. However, this approach is often not viable due to the scarcity of surveys covering workers' skills or measuring them in a way that is exhaustive enough. Even when such surveys exist, there are often issues like: (i) small samples; (ii) impossibility to measure variations over time if the survey is not repeated; (iii) lack of granular spatial data, such as NUTS3, or samples that are too small at the regional level to draw significant conclusions. These issues can be avoided using an approach based on the task-content of occupations.

In the "task-based framework", defined in Autor et al. (2003) and Acemoglu & Autor (2011), a task is a unit of work activity that produces output (goods and services). In contrast, a skill is a worker's endowment of capabilities for performing various tasks. The distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labour market conditions and technology (Acemoglu & Autor, 2011). Since an occupation is defined as a "set of jobs whose main *tasks* and duties are characterized by a high degree of similarity" (ILO, 2024) workers employed in a given occupation can be expected to have a rather homogeneous set of skills.[2] Approaches relying on the task-content of occupations usually merge two types of databases. The first is a "dictionary of

[2] Note that, although the two terms are often used interchangeably in the common language, occupation and job are not synonyms. ILO defines a job as "a set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self-employment" (ILO 2023). Hence, a person may be associated with an occupation through the main job currently held, a second job, a future job, or a job previously held.

occupations", i.e., a database containing a detailed description of all tasks (and the relative skills) required in each occupation. The second is a database containing the number of workers in each occupation in a given area or sector (e.g. the European Labour Force survey, national surveys, or administrative data). These two databases are then merged via the occupation codes, thereby providing a comprehensive picture of the skill composition in a given region. The more detailed the occupation classification is, i.e. the more "digits" it has, the more precisely the skills can be identified. As the tasks associated with various occupations evolve over time and across different countries, it is important that the dictionary is regularly updated and tailored to the specific country or region under analysis.[3]

However, detailed dictionaries of occupations are not very common as the costs involved in their production are significant. Overall, the most used dictionary of occupations is O*NET. The main issue with using O*NET is that it is specific to the US. Hence, when using O*NET for European microdata, researchers implicitly assume that the task-composition of each occupation is the same in the US and in Europe. In recent years, the Directorate-General for Employment, Social Affairs and Inclusion of the European Commission together with the European Centre for the Development of Vocational Training (CEDEFOP) developed a European Dictionary of occupations and skilled called ESCO (European Skills, Competences, Qualifications and Occupations). Section 3.3 provides more details on the ESCO, as it is the dictionary used in this study.

3. Data and methodology

The analysis is divided in four steps: (i) define the occupations involved in the hydrogen value chain; (ii) obtain regional employment data to assess the current set of workers' skills; (iii) define "similar" occupations; (iv) compute a regional measure of the skill mismatch.

3.1 Step 1: Define the occupations involved in the P2X value chain (target)

The first building block of the analysis revolves around defining the set of occupations involved in the hydrogen value chain. The analysis encompasses not only the workers required for the operation of

[3] For example, due to the arrival of ATMs and home banking, bank tellers do not perform the same tasks in their daily routine as they did 50 years ago. Furthermore, over time some occupations disappear altogether (e.g. chimney cleaners) while new ones arise (e.g. cybersecurity experts). As for space, a nurse in France is likely to perform slightly different tasks than one in Japan. For example, there might be some procedures that nurses are expected to perform in a country but not in the other.

the electrolysers, but also the workers employed in the renewable energy sector (RES) needed to power them. In particular, the focus is on solar and wind energy. Being electrolysation still a relatively new technology, defining the exact occupational mix needed in its production is not trivial. As there are no large-scale plants yet, it is not possible to observe which type of workers are involved and in which amounts. Moreover, several specific profiles do not even exist yet. Despite these challenges, a four-step approach has been developed to approximate the occupations likely to be required for hydrogen production, based on the current state of knowledge. The approach is summarised in Table 3-1. First, extensive desk research is conducted, scanning both academic and grey literature, to compile a comprehensive list of occupations expected to be necessary in hydrogen production. Examples of the sources reviewed include documents from France Hydrogène, the organisation bringing together public and private hydrogen stakeholders in France, and the US Department of Energy (France Hydrogène, 2021; U.S. Department of Energy, 2024). Second, in order to maximise the number of relevant occupations included in the analysis, this list is integrated with the list of hydrogen-related occupations scraped from *Stepstone*. Third, the full list of collected job titles is mapped to ESCO occupations. Finally, the resulting list is validated through interviews with experts to ensure its accuracy and relevance. The selection of the occupations involved in the RES is more straightforward, as this is a more mature sector and there is plenty of evidence regarding the requisite skills and number of workers needed to build and operate of solar and wind farms.

Both for electrolysers and RES, a distinction is made between the workers required for the construction of the facilities (capital expenditure, or CAPEX) and those needed for their subsequent operation and maintenance (operating expenditure, or OPEX). The distinction between CAPEX and OPEX is important because they require different skills but also a different *number* of workers. For instance, the CAPEX tends to be substantially more labour intensive. Furthermore, CAPEX and OPEX tend to have a different time horizon. The CAPEX phase typically involves a higher demand for labour during the initial investment and construction period, while the OPEX phase requires a more sustained, long-term workforce for ongoing operations and maintenance.

Table 3-1
Steps taken to identify the set of occupations involved in RES and P2X

Value chain phase	Approach
Electrolyser	Step 1: **Desk research** Step 2: Scrape *Stepstone* for **jobs related to hydrogen** Step 3: Map occupations titles from the previous steps into **ESCO occupations** Step 4: **Validate the list** we get from the previous steps by interviewing experts
Solar and wind energy sector	Step 1: **Desk research** Step 2: Match occupation titles to **ESCO occupations**

Source: DIW Econ.

The final *number* of target workers is a function of the desired electrolysis capacity. In order to assess the preparedness of each region from a labour force point of view, irrespective of their specific need for hydrogen or potential for renewable energy generation, the study investigates a scenario in which each region aims to achieve an electrolysis capacity of 125 megawatts (MW).

3.2 Step 2: Define the potentially employable local workforce

The second step of the analysis aims at identifying the pool of workers which could potentially be employed in the hydrogen production chain. To this end, it is assumed that a considerable proportion of workers in certain sectors are unlikely to leave their current occupations for positions in the renewable energy or hydrogen production sectors. Hence, the analysis focuses only on workers currently employed in sectors that are projected to experience a decline in employment in the near future, for instance as a result of the transition to green energy or the increasing use of digital technologies and automation. The identification of these workers is based on the *CEDEFOP Skill forecast*, which provides estimates of employment variation until 2035 by Country and 2-digit NACE sectors based on a series of macroeconomic assumptions concerning: (i) population projections; (ii) both short and long-term GDP projections; (iii) the EU Green Deal; (iv) automation and digitalisation trends (Cedefop, 2024).[4]

CEDEFOP's employment projections are used to identify as "declining" the sectors that between 2019 and 2035 are expected to lose more than 10,000 workers and that are projected to decline at a rate greater than the overall decline in the workforce, namely 4.86%. To know which set of skills do workers

[4] For more details see CEDEFOP's technical and methodological reports (Cedefop, 2023a, 2023b).

from these sectors possess, it is first necessary to identify their occupations. To this end, the study relies on detailed regional (NUTS3) employment data, including 4-digit ISCO-08 occupations for workers in the declining 2-digit NACE sectors, from the German Federal Employment Agency (*Bundesagentur für Arbeit*). As older individuals are unlikely to engage in re-skilling activities due to their proximity to retirement, the analysis is limited to workers under the age of 55.

3.3 Step 3: Define "similar" occupations

After having defined the occupations needed in the hydrogen production and the occupations of the available workers in each region, the third step focuses on matching the corresponding skills using the European dictionary of occupations and skills ESCO (European Commission, 2024a). ESCO has a series of convenient features. First, it is specific to European labour markets. Second, it is updated frequently. Since its launch in July 2017 there have been about ten revisions. This study used the version v1.1.1. Third, the occupation classification is built on the ISCO-08 classification, thereby allowing an easy merge with employment data released by Eurostat, national statistical offices, or employment agencies. Fourth, it can be easily downloaded free of charge in 28 languages.

ESCO is built around two pillars: occupations and skills. The occupations pillar is based on ISCO-08. At its most detailed level, the 4-digit level, the ISCO-08 classification encompasses 436 distinct occupations. ESCO adds an additional disaggregation with 3008 occupations. Of these, 1,760 are at the 5-digit level. The others are nested detailed occupations, going up to the 8-digit level. It should be noted that not all 4-digit occupations have sublevels that are nested up to the 8-digit. Indeed, a considerable number of these do not extend beyond the 5-digit.

The skills pillar covers 13,890 concepts, structured in the following four sub-classifications: (i) "K - knowledge"; (ii) "L - language skills and knowledge"; (iii) "S - skills"; and (iv) "T - transversal skills". As the goal of this study is to assess the skill-gap for rather technical occupations, the focus is restricted to the concepts belonging to "S - skills" and "K - knowledge". These skill concepts are organised into two separate hierarchies. Roughly 10,000 level-4 skills are organised into 296 level-3 skills, 74 level-2 skills, and 8 level-1 skills. Similarly, approximately 3,000 level-4 knowledges are nested into 86 level-3 knowledges, 29 level-2 knowledges, and 11 level-1 knowledges.

3.3.1 Skills-Occupation and Knowledges-Occupation matrices

For each occupation, ESCO produces a series of skill-occupation matrices and a knowledge-occupation matrices. Each of these matrices reports which share of the level-4 concepts falls into each higher-level

group. For example, Figure 3-1 illustrates the content of the skill-occupation and the knowledge-occupation level-3 matrices for one of the declining sectors' 4-digit occupations, i.e., "8111 – Miners and quarriers". The largest share of level-4 skills required in the occupation belong to the level-3 "Operating mining, drilling and mineral processing machinery" (19.3%), while the largest share of level-4 knowledges needed belong to the level-3 "Mining and extraction" (25%). The exact approach taken by ESCO in building the matrices is described in detail in ESCO (2021).

The analysis relies on two of these matrices: the matrix for 4-digit occupations and level-3 skills, and the matrix for 4-digit occupations and level-3 knowledges. A few adjustments are imposed to improve the quality of the final skill-distance measure:

- The skill shares of occupations that can be performed also in academia (e.g. chemist) tend to be heavily skewed towards "purely academic" skills, such as "academic writing" or "apply to research funding". This leads to similar skills shares for occupations that are quite different outside academia, such as "biochemist" and "political scientist". This issue is mitigated by removing all skill shares from "S2.1.1 conducting academic or market research" and "S1.13.3 technical or academic writing". For similar reasons, also a few rather generic skill groups are removed, namely "S1.2.1 communicating with colleagues and clients", "S1.2.3 developing professional relationships or networks", "S1.9.1 developing solutions", and "S1.8.1 working in teams". The remaining skill groups are rescaled so that they sum again to 100.
- Following a similar logic, all level-3 knowledge areas nested within the level-1 category "00 - generic programmes and qualifications" are removed from the knowledge-occupation matrix, as these represent broad, transversal knowledges typically acquired through primary and lower secondary education programs. The remaining knowledge groups are rescaled so that they sum again to 100.
- Finally, the two matrices are appended weighting skill-shares by 0.6 and knowledge-shares by 0.4, so that the sum of skill and knowledge shares for each occupation sum to 100.[5] For simplicity, the term "skill" is used throughout the rest of the report to refer to the combined set of ESCO skills and knowledges.

[5] The final results are very similar when weighting both components by 0.5. Slightly more importance is given to the skills as they have more variation and are more likely to be shared between different occupations.

3.3.2 Skill distance measure

The final matrix of skills is used to create a matrix of bilateral skill-distance measures across all couples of occupations. Specifically, for each couple of occupations *i* and *j*, each possessing a set of skills k, the bilateral skill-distance is measured as:

$$Distance_{i,j} = \sum_{k=1}^{K} |s_{i,k} - s_{j,k}|$$

where $s_{i,k}$ is the skill-share of level-3 skill *k* for occupation *i*. The skill distance is re-scaled to range from 0 (exact same set of skills) to 100 (completely different set of skills). It shall be remarked that $s_{i,k}$ is not properly a measure of each skill-group *importance* within an occupation as, unfortunately, ESCO does not contain this sort of information at the moment. However, while not perfect, $s_{i,k}$ is arguably a reasonably good approximation of the skill-group's *importance* within each occupation.

Figure 3-1
Example of top entries in ESCO Knowledges and Skills matrices for a 4-digit occupation

ESCO Occupations Pillar

Occupation
8 - Plant and machine operators and assemblers
81 - Stationary plant and machine operators
811 - Mining and mineral processing plant operators
8111- Miners and quarriers
8112 - Mineral and stone processing plant operators
8113 - Well drillers and borers and related workers
8114 - Cement, stone and other mineral products machine operators

ESCO Skills Pillar

Skills	(%)
Operating mining, drilling and mineral processing machinery	19.32
Complying with health and safety procedures	10.23
Installing wooden and metal components	9.09
Operating pumping systems or equipment	7.95
Using hand tools	6.82
Repairing and installing mechanical equipment	6.82
Operating petroleum, chemical or water processing systems or equipment	5.68
Cutting materials and drilling holes	4.55
Operating earthmoving equipment	3.41
Operating lifting or moving equipment	3.41
...	...

Knowledges	(%)
Mining and extraction	25.00
Mechanics and metal trades	17.86
Occupational health and safety	17.86
Electricity and energy	14.29
Chemistry	7.14
Earth sciences	7.14
Building and civil engineering	7.14
Biology	3.57
...	...

Notes: the left-side of the picture reports occupations at the 4-digit ESCO (ISCO-08) level. The occupation-skill (occupation-knowledge) on the right show the share of level-4 skills (knowledges) nested within each level-3 skill (knowledge).

Source: DIW Econ on ESCO data.

Computing skill-based distance measures for couple of occupations is not a novel exercise, as similar methodologies have been employed in various studies (Bechichi et al., 2018; Bowen et al., 2018; Consoli et al., 2016; Grundke et al., 2017; Neffke et al., 2024). The approach adopted in this report, however, offers distinct advantages: (i) the use of European data instead of the US-based O*NET; (ii)

the computation of measures based on a comprehensive set of roughly 300 skill groups, rather than the heavily aggregated skill measures, such as cognitive or numeracy skills from the PIAAC (Programme for the International Assessment of Adult Competencies); and (iii) the use of updated skills compared to the BIBB (*Bundesinstitut für Berufsbildung*) survey.

3.4 Step 4: Compute a regional measure of the skill gap

For each region, the first step of the analysis defined a set of occupation quotas, i.e. a list of target occupations and the number of workers needed in each one of them (e.g. 31 “Civil Engineers”; 91 “Surveying technicians”; 113 “Electricians” and so on). The fourth step deals with filling each of these quotas with the closest available workers in each region, selected from the pool defined in the second step. The proximity of these workers is determined based on the distance measure defined in the third step. Table 3-2 reports an example of the algorithm applied. The first three occupation quotas are filled without issues as the number of available workers in the region is larger than the quota. For the occupation “Mechanical machinery assemblers” things are more complicated as 91 workers are needed while the region only has 48. The closest occupation with available workers is “Mechanical engineering technicians”, with a skill-distance of 38.6. However, while the region has 50 workers in this occupation, only 18 workers are still available, as 32 were already assigned to fill the quota for “Mechanical engineering technicians”. Hence, following the allocation of these remaining 18 workers, the final 25 workers required are sourced from the category of "Structural-metal preparers and erectors", with a distance of 42.5. The final weighted skill gap (WSG) index is computed by taking a weighted average of the distance between the assigned workers and the target ones, in which the weights are given by the number of workers in each group. For example, the WSG for Table 3-2 would amount to:

$$WSG\ Index = \frac{(91 \cdot 0) + 2 \cdot (32 \cdot 0) + (48 \cdot 0) + (18 \cdot 38.6) + (25 \cdot 42.5)}{91 + 32 + 32 + 48 + 18 + 25} = 7.1$$

The algorithm belongs to the family of greedy algorithms, which short-slightly search for the best local optimum. While there are algorithms that are best suited to find the *global* optimum, these are much more computationally demanding, especially in a setting with a large matrix of target and origin occupations to be optimised for 400 regions. Moreover, the greedy algorithm has been found to perform reasonably well in simulations (Güneri et al., 2019).

It should be remarked that this exercise captures a sort of best-case scenario in which each worker can get re-allocated to the most suitable occupation. Of course, in reality personal aspirations also play an

important role and it will be the case that a certain share of workers would rather migrate or decide to re-train for another occupation.

Table 3-2
Example of greedy matching algorithm

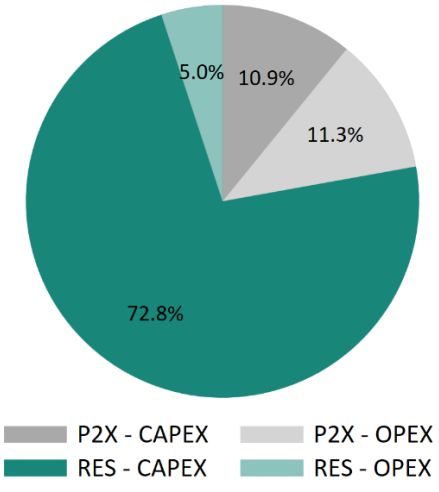
Target Occupation	Target workers	Available Occupation in the region	Available workers	Assigned workers	Skill. Distance
Building construction labourers	91	Building construction labourers	196	91	0
Electrical and electronic equipment assemblers	32	Electrical and electronic equipment assemblers	36	32	0
Mechanical engineering technicians	32	Mechanical engineering technicians	50	32	0
Mechanical machinery assemblers	91	Mechanical machinery assemblers	48	48	0
		Mechanical engineering technicians	18	18	38.6
		Structural-metal preparers and erectors	136	25	42.5

Source: DIW Econ.

4. Results

When evaluating labour force allocation and potential skill gaps for future economic activities, it is crucial to account for the uneven distribution of workers across different stages of the value chain. For instance, in the hydrogen production sector analysed in this study, it is estimated that 77.8% of the total workforce will be needed in the renewable energy sector, while only 22.2% will be required for the P2X (Figure 4-1). Furthermore, during the CAPEX phase, most of the workforce will belong to the RES, whereas in the OPEX phase, around two-thirds of the workforce will be needed in the P2X sector.

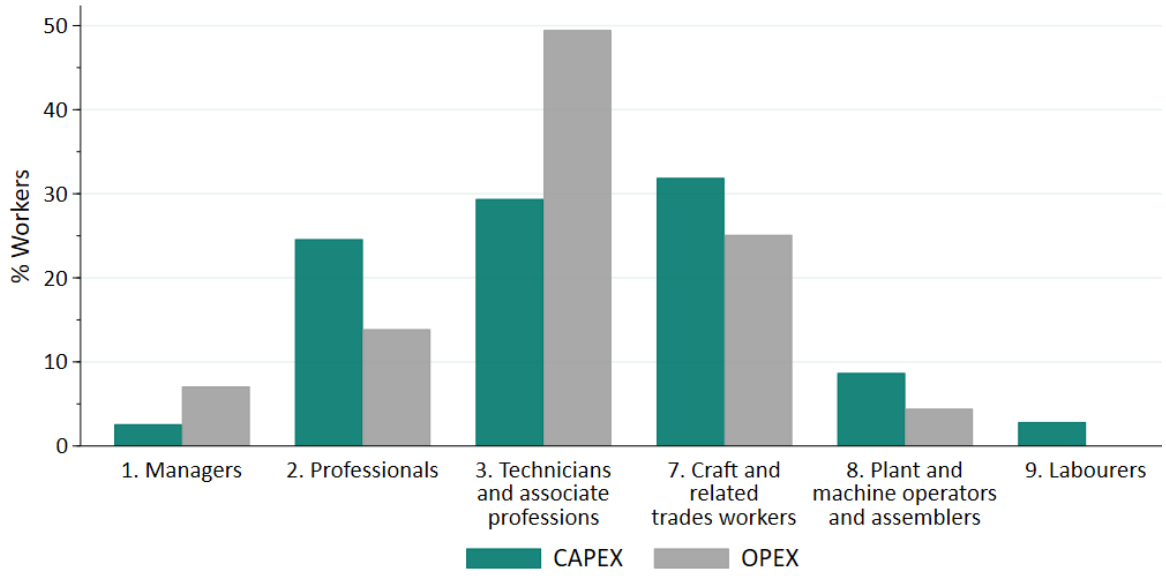
Figure 4-1
Distribution of the target workforce by phase of the value chain



Source: DIW Econ.

The distinction between CAPEX and OPEX is particularly important because their workforce distribution across the six broad occupational groups, each demanding different skill sets, is different. In the CAPEX phase, the workforce is fairly evenly spread among professionals, technicians, and trades workers, while in the OPEX phase the demand shifts heavily toward technicians (Figure 4-2). Differences across CAPEX and OPEX are also important as their demand of workers has a different time horizon. The CAPEX phase typically involves a higher demand for labour during the initial construction period, while the OPEX phase requires a more long-term workforce for ongoing operations and maintenance. Therefore, knowing the number of workers required in each phase, their occupational profiles, and the timing of their deployment is of key importance to prevent workforce availability bottlenecks.

Figure 4-2
Distribution of CAPEX and OPEX target workforce by broad occupational group

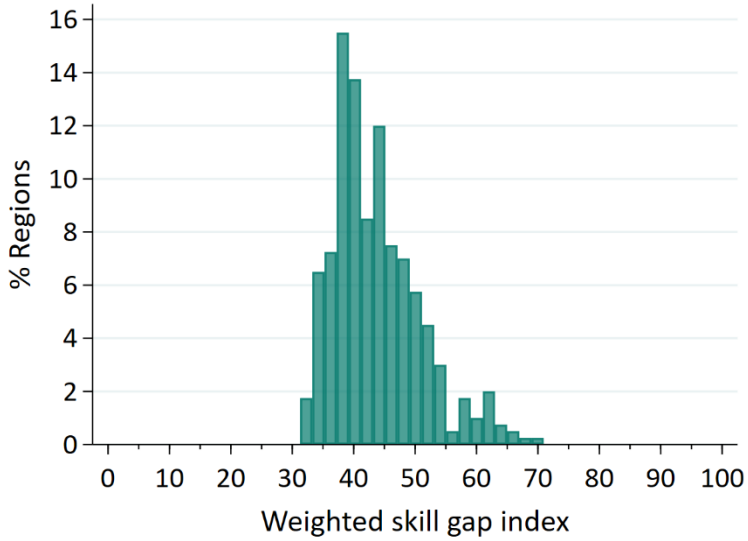


Note: the bars for each phase sum up to 100.

Source: DIW Econ.

To assess each region's preparedness, the study investigates a scenario in which each region aims at an electrolysis capacity of 125 MW. Figure 4-3 shows the distribution of the WSG index across the 400 regions. The average region has a WSG index of 43.7. However, there is considerable variation, with the best region scoring 31.3 and the worse 70.9.

Figure 4-3
Distribution of the WSG index across regions

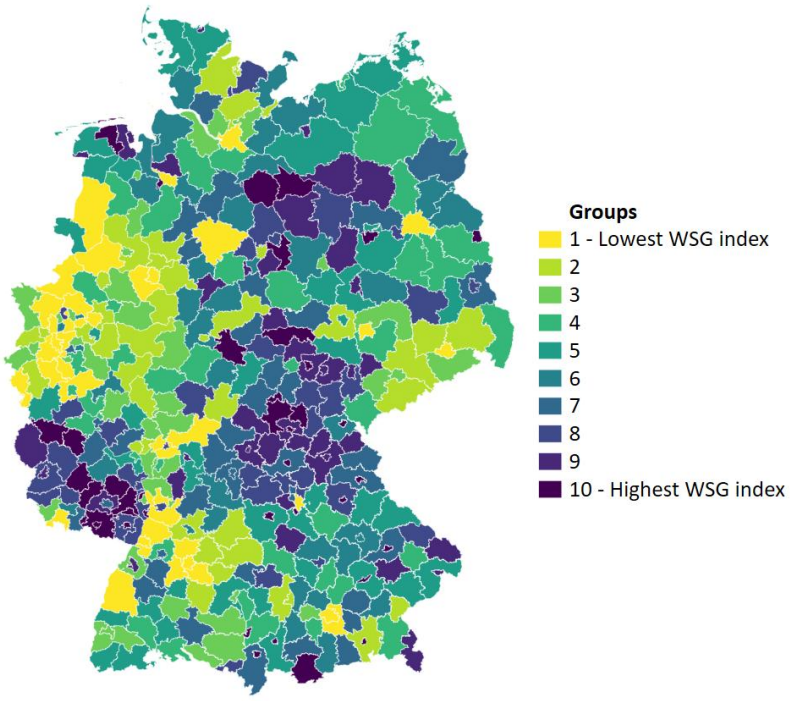


Note: the WSG index ranges from 0 (no skill gap) to 100 (large skill gap).

Source: DIW Econ.

In terms of spatial distribution, Figure 4-4 reveals the existence of clear geographical clusters. Specifically, the most prepared regions are situated in areas with a strong manufacturing tradition, particularly in the Ruhr area in the north-west and in the automotive industry in the south-west. In contrast, the least prepared regions are located in the centre and centre-west, in mostly rural areas.

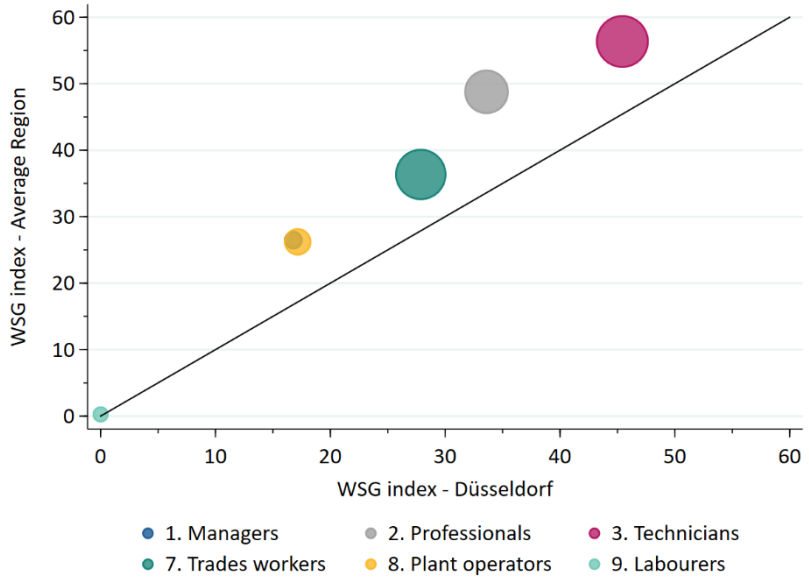
Figure 4-4
Regional WSG Index ranking



Source: DIW Econ.

To understand the factors driving these significant regional differences, Figure 4-5 compares the index at the broad occupation level for a region in the best performing decile ("Düsseldorf", WSG index: 33.2) with the average across all regions. Each bubble represents a target broad occupation, with larger bubbles indicating larger target employment quotas. The x-axis reports the WSG index for each occupation in Düsseldorf, while the y-axis reports the index in the average region. Therefore, each bubble above the 45' line indicates a better performance of Düsseldorf compared to the average. The large difference in the regional WSG index is largely driven by technical middle and high-skilled occupations, namely those belonging to the broad occupation groups "3. Technicians and associate professionals", and "2. Professionals", respectively. These dynamics explain the regional clusters observed in Figure 4-4 as the manufacturing regions have more abundancy of workers with technical middle and high-skilled profiles.

Figure 4-5
Difference in the weighted skill gap index by 2-digit occupations for a top decile vs. bottom decile region



Note: the size of the bubbles reflects the number of target workers in the broad occupation group. The WSG index ranges from 0 (no skill gap) to 100 (large skill gap).

Source: DIW Econ.

5. Conclusion

Global megatrends are expected to significantly reshape labour markets worldwide. Policy makers need to anticipate how workers with specific skill sets can move into new roles, such as those required following the green transition, while adapting to the decline of jobs in declining occupations.

The present study proposes a skill-based approach to measure skill gaps leveraging a detailed dictionary of occupations and skills (ESCO) combined with employment data at the sectoral-occupational level. Using a matrix of bilateral skill distances, the approach enables the evaluation of the gap between current or projected skills and the target skill sets needed in a given scenario. The method is versatile and could also be used in several contexts, such as assessing the transition of coal workers to renewable energy jobs.

Applying this approach to the hydrogen sector in Germany, the study provides a rough estimate of how prepared each NUTS3 region's workforce is for a targeted electrolysis capacity of 125 MW. The analysis reveals the existence of clear geographical clusters. In particular, the most prepared regions are situated in areas with a strong manufacturing tradition, particularly in the Ruhr area in the north-west and in the automotive industry in the south-west. In contrast, the least prepared regions are located in the centre and centre-west, in rural areas. Disaggregating the index at broad occupation level shows that the advantage of the most prepared regions is driven by their ability to easily fill the target quotas for technical middle and high-skilled occupations. These dynamics explain the regional clusters, as the manufacturing regions have more abundancy of workers with technical middle and high-skilled profiles.

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