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A Comparison of Alternative Methodologies

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Abstract

As the green transition is set to accelerate swiftly over the next decades, its implications for labour markets and workers are of key concern to policymakers. The aim of this paper is to review different methodologies to identify green jobs in cross-country comparable data that are regularly and timely available for EU Member States and assess their usefulness for policy-relevant labour market analysis. Three different methodologies are compared, of which one draws on Eurostat's environmental accounts (EGSS) data. The two other methodologies use EU Labour Force Survey (LFS) data to implement task-based approaches. The first task-based approach uses information on occupational task profiles from O*NET data, in line with several other existing studies. The second task-based approach uses a more novel source of information on occupational skills profiles, notably the European Classification of Occupations, Skills and Competences (ESCO). Two out of the three indicators show a rising trend in green jobs over recent years. Sectors such as industry, construction and agriculture account for the bulk of the green jobs; even if the proportion of service jobs among green jobs is on the rise. Green jobs are more likely to be taken up by men than non-green jobs. The geographical and skills distributions of green jobs depend on the methodology used. Based on the presented analysis, the national accounts (EGSS)-based approach seems the most reliable. Nevertheless, given its constraints in terms of opportunities for socio-economic analysis, it still seems useful to consider other approaches to get at richer insights, while consistently verifying the robustness of results across different methodologies.

JEL Classification: 21, J23, J24, L52, Q28.

Keywords: green jobs, task-based approach, environmental accounts, ESCO, O*NET.

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ABBREVIATIONS

EGSS	Environmental goods and services accounts
ESCO	European Classification of Occupations, Skills and Competences
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
LFS	EU Labour Force Survey
NACE	Statistical Classification of Economic Activities in the European Community
NUTS	Nomenclature of Territorial Units for Statistics
O*NET	US Occupational Information Network database
SOC	Standard Occupational Classification

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1. INTRODUCTION

As the green transition is set to accelerate over the next decades, its implications for labour markets and workers are of key concern to policymakers. A central question is whether it will have negative impacts on workers in highly polluting economic activities, through job losses or obsolescence of skills, pushing up structural unemployment. This issue was addressed in Vandeplas et al. (2022) even if precise assessments of future developments in this area remain a challenge.

Another important concern is whether the necessary labour reallocation towards greener activities will proceed smoothly or be hampered by skills shortages. This is a question that is even more difficult to address, especially because of challenges encountered in defining, identifying and measuring green jobs and skills needs. Another complicating factor is that labour and skills shortages are at an all-time high at present in the EU, for a variety of reasons, including longer-term demographic developments, which are difficult to disentangle from the skills shortages arising specifically from the green transition.

As set out in the Staff Working Document accompanying the 2020 Communication on "Stepping up Europe's 2030 climate ambition", an European Commission estimate suggests that with the right policies in place, the green transition could on aggregate create around 1 million additional quality jobs in the European Union by 2030 and 2 million by 2050.[1] While job losses are expected in some mining activities and fossil-fuel based energy production, new job opportunities are expected in the circular economy activities and sustainable transport and energy production. By creating quality jobs, the green transition can contribute to raising incomes and reduce social exclusion – provided Member States follow region- and ecosystem-specific approaches to shape appropriate policy packages, in liaison with social partners, local and regional authorities, and other stakeholders.[2]

Being able to identify green jobs in labour market data helps to better understand the speed at which labour markets are greening, the regional distribution of green job creation, job characteristics such as wages and job quality, and skills requirements for green jobs. To this extent, this paper reviews three different methodologies to identify green jobs in labour market data and compares the results from each methodology. The choice of methodologies is driven by the desire to draw strictly on cross-country comparable data that are regularly and timely made available for EU Member States and can be used for policy-relevant labour market analysis.

The paper focuses on green jobs in a relatively narrow sense, considering those jobs that are either part of a green production process (e.g. producing solar panels), have an explicit green aim, such as reducing the impact of human or economic activity on the environment (e.g. waste recycling), or have a certain green task content (e.g. implementing environmental regulations). Within the task-based approach, other studies have considered wider concepts, by including for instance jobs that do not imply any green tasks but that would be expected to see employment growth as a result of the green transition (e.g. public transport drivers) (see e.g. Bowen and Hancké, 2019). A recent paper by Urban et al. (2023) provides a broad qualitative overview of other possible definitions and classifications of green jobs, albeit without presenting concrete figures according to the different approaches.

An important qualification is that there is an issue of overlap between how green and brown jobs are defined in the literature (see Section 6 for a more detailed discussion). Indeed, jobs involving green tasks may often be found in highly polluting activities, which are most likely to be subject to environmental regulation and therefore require job holders to take action to comply with those regulations and reduce the activities' impact on the environment. A possible 'ad-hoc' way out would be to simply remove jobs in the overlap between brown and green jobs (as done by e.g. Bluedorn et al. 2022), but this paper has opted not to take that route and instead maintain the overlap, to avoid missing out on a significant proportion of green jobs, and to underline the nontriviality of defining green jobs.

[1] Staff Working Document from the Commission, Impact Assessment accompanying the Communication 'Stepping up Europe's 2030 climate ambition - Investing in a climate-neutral future for the benefit of our people', SWD(2020) 176 final. Projections based on EQUEST using a 'lower taxation low-skilled labour' scenario.

[2] Council Recommendation of 16 June 2022 on ensuring a fair transition towards climate neutrality 2022/C 243/04.

Each of the three methodologies reviewed in this paper draws on data collected by Eurostat for all EU Member States. The first method builds on the European environmental goods and services accounts data, also presented in Vandeplas et al. (2022). The second method draws on EU Labour Force Survey (LFS) data and mimics a method previously used in the literature by, inter alia, Vona et al. (2018), Gilli et al. (2020), Bluedorn et al. (2022), Scholl et al. (2023), and OECD (2023), using information on jobs' green task content from the US Occupational Information Network database (O*NET).[3] The third method also draws on LFS data, and combines it with recently released information on jobs' green task content from the European Classification of Occupations, Skills and Competences (ESCO).[4] To the best of our knowledge, this is the first research paper to link ESCO green skills to LFS data for EU labour market analysis.

2. OVERVIEW OF THE CONSIDERED METHODOLOGIES

In what follows, the three methodologies and their analytical basis are discussed. In addition, a brief overview is presented of the results they suggest on the importance and evolution of green jobs in the EU over the last decade.

2.1. EGSS-BASED METHODOLOGY

The first methodology relies on data from Eurostat's environmental accounts data. Eurostat collects data from Member States on gross value added and employment in the *environmental goods and services sector (EGSS).* This sector brings together activities that produce goods and services for environmental protection or for resource management (e.g. electric vehicles, catalysts, pollutant filters, waste treatment services, noise insulation works…) and spans different economic activities (especially sewerage and waste management, but also manufacturing and construction). These data allow for a definition of green jobs as jobs in environmental protection and resource management at the level of institutional units based on their activities and their products, whereas institutional units can combine jobs defined as green jobs with jobs defined as non-green jobs.[5] The EGSS methodology follows the international standard of the system of environmental economic accounts (SEEA) and has been developed in a collaboration between the United Nations, the European Union, the FAO, the IMF, the OECD and the World Bank, with the explicit intention of:

> '*assessing (a) the potential for economic activity and employment to be based on environmentally friendly and more resource-efficient activities and (b) the extent to which the economy is responding to various public policies and initiatives that have this objective in mind.'* (UN, 2014: 111)

Hence, the choice of the definition is attractive as it is widely recognised and accepted, and the purpose of the data collection aligns with the purpose of this paper, notably identifying jobs that can be linked to the green transition as to measure their growth and impact. It is also in line with the definition of green jobs by the International Labour Organisation (ILO), which is the only international definition of green jobs.[6]

In the United States, the Bureau of Labor Statistics (BLS) has developed an accounting methodology of green jobs with a similar scope.[7] What is appealing about the EGSS and BLS measures is that they consider the *purpose* and the *process* of economic activities - e.g. employment in the production of solar panels would be classified as green even if the task content of these jobs would not be very different from jobs in the production of other manufacturing goods.

[3] https://www.onetonline.org/

[4] https://esco.ec.europa.eu/en

[5] More technical details are provided in Eurostat (2016).

[6] The ILO definition reads as follows: "*Green jobs are decent jobs that contribute to preserve or restore the environment, be they in traditional sectors such as manufacturing and construction, or in new, emerging green sectors such as renewable energy and energy efficiency.*" (see: https://www.ilo.org/resource/article/what-green-job) The only notable distinction is that the ILO definition only considers "decent" green jobs, while the EGSS definition does not distinguish between decent and non-decent jobs.

[7] See https://www.bls.gov/green/home.htm#definition

EGSS employment data are made regularly available, albeit with a significant time lag.[8] Breakdowns by economic activity (NACE-1D level) are available for all Member States but not for the EU aggregate. A particularly interesting feature of the EGSS data is that data are also broken down, to some extent, by purpose, notably with regard to environmental protection[9] and with regard to resource management.[10] This allows tracking, for instance, the number of green jobs in the management of energy resources. While EU aggregate data are not directly available, they can be approximated as a simple sum of available Member State-level data.[11]

Based on the EGSS methodology, 2.7%[12] of employment was classified as green in the EU27 in 2021 (the latest year of available data). This figure is of the same magnitude as US-based estimates drawing on the BLS Green Good and Service Survey, which indicated 2-3% of US employment concerned green jobs in 2010-11 (Vona et al., 2018; BLS, 2013).

An important limitation of the EGSS methodology is that no data are available at the micro-level that would allow for breakdowns by more detailed job or worker characteristics than the ones mentioned above. This limits the potential of these data to examine distributional aspects (e.g. across regions or worker characteristics) or job quality, which are nevertheless key to understand the social implications of the green transition. Therefore, in what follows, two alternative methodologies are explored that identify green jobs at the occupational level in LFS data based on green task content and/or green skills requirements.[13] LFS data are available at the micro-level and allow for breakdowns along various job and worker characteristics.

2.2. O*NET-BASED METHODOLOGY

The second methodology relies on combining data from the European LFS with insights from O*NET, the main source of occupational information in the US. O*NET provides detailed descriptions of occupations, including their task content and skills requirements, and can be linked to the US SOC2010 occupational classification for estimates of employment by occupation.[14] Dierdorff et al. (2009) have complemented O*NET with a taxonomy of green occupations for the US. This taxonomy allows to tag more than 200 occupations at the SOC 8-digit level as "green" across three categories, reflecting the expected impact of the green transition. A first category of '*green new and emerging*' jobs comprises new occupations directly related to the green economy, such as solar energy systems engineers. A second category of '*green enhanced skills*' jobs covers existing occupations that see their tasks change due to the green transition, such as urban and regional planners. Finally, the job category of '*green increased demand*' consists of occupations which are not expected to see substantial change in their task content but see labour demand increase as a result of the green transition. The latter category includes more general occupations, such as customer service representatives. Together, these three categories of "green" jobs account for almost 20% of US employment (cfr. Bowen et al. 2018).

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[8] By the 2024Q1, only a few EU Member States made 2022 data available. According to Regulation 691/2011, Member States have 24 months' time to submit their data.

[9] The Classification of Environmental Protection Activities (CEPA 2000) was developed by the UN Statistical Commission and discerns for instance activities related to waste management, air pollution, biodiversity etc. For more details, see Eurostat (2016).

[10] The Classification of Resource Management Activities (CReMA) was developed by Eurostat Task forces and distinguishes between management of water, forest, minerals, energy etc. For more details, see Eurostat (2016).

[11] Data on IT are available as of 2016, on HU as of 2017, and on SK and CY as of 2018. For SE, some of the more disaggregated categories are missing until 2021.

[12] This figure reflects the share of green jobs (in fulltime equivalents) over employment in fulltime equivalents. Employment data are taken from Eurostat's national accounts data, and adjusted using data from LFS on the proportion of part-time workers and usual working hours in part-time jobs.

[13] Note that in practice, the conceptual difference between *tasks* and *skills* is smaller than one might expect, as skills are often formulated as the ability to perform certain tasks, and tasks define the demand for certain skills. Therefore, the terms 'tasks' and 'skills' will be used interchangeably in this paper.

[14] The Standard Occupational Classification (SOC) is the occupational classification used in the US: https://www.bls.gov/soc/home.htm.

Vona et al. (2018) propose a narrower definition of green jobs by applying an additional filter to the set of green occupations identified by Dierdorff et al. (2009) to focus exclusively on jobs *directly involving green tasks.* In O*NET, each occupation is described by a bundle of tasks. Among these tasks, some are directly related to improving environmental sustainability and reducing greenhouse gas emissions. Using this information, a *green task intensity score* can be calculated for each occupation as the *proportion of green tasks to total tasks.* Occupations without any green tasks are assigned a zero score. As a result, green jobs are jobs that are identified by Dierdorff et al. (2009) as relating to the green economy *and* include green task content. This approach is also adopted by Vona (2021) and Bluedorn et al (2022). 'Green increased demand' jobs as defined by Dierdorff et al. (2009) do not include green tasks and thus are not considered as green occupations in the work by Vona, Bluedorn and their co-authors.

The combination of O*NET information and LFS data presents a number of important challenges at the technical level. Given that O*NET is using the US occupational classification, to apply it to EU LFS data, it must be translated through a so-called 'crosswalk' to ISCO-08, the occupational classification used in the EU. Furthermore, Eurostat only makes EU Labour Force Survey data available at the relatively aggregated ISCO-08 3-digit level. This means that some information may be lost in the process of aggregation.[15] The crosswalk and aggregation steps imply a number of impactful methodological choices and simplifying assumptions.[16] For comparability with previous research, this paper draws on work by Bluedorn et al. (2022) who have made their results on green task intensity scores at ISCO 3-digit level publicly available.

The literature has put forward two different ways to arrive at an estimate of the share of green jobs in the economy. The most straightforward way would be to transform the green task intensity scores into a discrete binary variable (green versus non-green jobs) by defining green occupations as those occupations with a green task intensity score above a certain threshold. The advantage of such an approach is that specific jobs can be identified as "green" or "non-green" and this facilitates a further in-depth characterisation of green jobs (e.g. sectoral, regional distribution, skills requirements, …) and workers in those jobs. Following Vona et al. (2018), a threshold green task intensity score of 10% is used in this paper, which means that occupations with a score above 10% are classified as green.[17] Raising the threshold above 0 avoids including occupations for which green tasks constitute only a marginal proportion of task content.

At the same time, researchers in the field have argued that the binary transformation involves a significant loss of useful information and variation (for instance the fact that no distinction is made between jobs with a green task intensity score of 10% and jobs with a score of 30%); and they have advocated for an alternative approach. Notably, Vona et al. (2018) propose using the average green task intensity score, expressed in percent, as a proxy for the proportion of green occupations in total employment, arguing that the binary approach would lead to over-estimation of the proportion of green jobs.

The two approaches can be applied using LFS data. At the 3-digit level of ISCO-08, at which European labour market data are available, 130 different occupational groups can be discerned. Using the O*NET green occupations classification, the green task intensity scores for these occupations range from 0 to 38.7%, with a median of 0%.

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[15] Internal analysis in DG EMPL and DG JRC compared results from defining green jobs at the ISCO-3 digit and ISCO-4 digit level respectively and found that the impact on the proportion of green jobs is not substantial.

[16] E.g. regarding the use of simple averaging or employment weighted averaging in aggregation (which also depends on available employment data: employment-based weighting routines usually draw on US data as no data are available for the EU at the required level of disaggregation), or regarding the management of many-to-many mapping needs in the crosswalk between SOC and ISCO schemes. Different choices or assumptions are likely to have a meaningful impact on the results of the exercise. At the same time, Scholl et al. (2023) suggest, based on the exploration of a number of variations of O*NET-based measures, that the measurement of green jobs is reasonably robust to different methodological choices with regard to weighting and mapping.

[17] OECD (2023) also uses a threshold of 10%. Other choices are possible here as well: for instance, IMF (2022) applies a threshold at 0: they consider every occupation with a strictly positive green task intensity score (and a zero-pollution intensity) as green. Scholl et al. (2023) apply a threshold at zero as well.

In a binary definition, 11 out of 130 occupations at the ISCO 3-digit level have a green intensity score exceeding 10% according to the O*NET-based definition (see Table 2).[18] Together, these occupations represent approximately 7.5% of employment in the EU27 in 2022 (the latest year of available data). It is important to note that different task-based methodologies based on O*NET may arrive at different estimates, including because of specific choices made with regard to data aggregation and the implementation of required crosswalks between occupational classifications used in the US (SOC) and the EU (ISCO).

Using the continuous approach would reduce this figure to 2.4%, more in line with the proportion of jobs identified as green based on the EGSS methodology. Hence, in line with concerns by Vona et al. (2018), the binary approach thus indeed leads to higher estimates of the proportion of green jobs as the continuous approach. At the same time, as it identifies the prevalence of green skills in employment as a whole, rather than identifying green occupations as clearly delineated units of analysis, using the continuous approach complicates descriptive (and more advanced) analysis of the characteristics of jobs and workers. This is why this paper applies a binary definition of green jobs instead.

2.3. ESCO-BASED METHODOLOGY

The third methodology makes use of information from the European multilingual Classification of Skills, Competences and Occupations (ESCO), which was first launched in 2017 as the first effort to develop a standard terminology on occupations and skills at the European level. ESCO provides descriptions of occupations and the associated skills requirements for more than 3000 occupations, following the structure of the International Standard Classification of Occupations (ISCO-08), the standard occupational classification used in the EU by EUROSTAT, including in its Labour Force Survey. ESCO is publicly available in 28 languages.

While ESCO does not address directly the definition of green jobs, nor include information on which jobs are more or less affected by the twin transition, recently, efforts were undertaken to label skills and knowledge which relate to reducing the impact of human activity on the environment as "*green*" in ESCO, in line with a definition proposed by Cedefop (2012).[19]

The green labelling exercise distinguishes between *skills/competences* (e.g. conducting energy audits, training staff on recycling programmes, designing heat pump installations but also transversal skills such as evaluating the environmental impact of personal behaviour) and green *knowledge* concepts (e.g. knowledge on emission standards).[20] In the remainder of this paper, however, no difference will be made between green *skills* and *knowledge*; they will be jointly considered as *green skills,* and treated or interpreted in a similar way as green tasks in the O*NET framework.

In ESCO, occupations are described at a more granular level than the level of detail available in ISCO-08 (4-digit level unit groups).[21] Nevertheless, using tailor-made ESCO Skill-Occupation Matrix Tables, ESCO-based skills information can be linked to ISCO-08 at the 4-digit level. This allows for the calculation of the proportion of green skills in the total number of skills for each occupation group, in line with the exercise

[18] In comparison, 38 occupational groups at the ISCO-3D level have a green intensity score above 0 following the O*NET approach. With a binary definition defining all occupations with a non-zero (O*NET-based) green intensity score as green occupations, these would cover 37.9% of employment in the EU. Dropping occupations identified as 'brown' by Bluedorn et al. (2022) would mean green occupations would still cover 24.7% of employment in the EU.

[19] Skills and knowledge concepts were labelled as green based on their description, using a combination of human intervention and machine learning techniques. A first step involved manual labelling. A second step involved labelling by a pre-trained classification algorithm which was fine-tuned on a training dataset based on definitions from official classifications, job vacancies, European and national legislation, and reports. In a third step, both classifications were compared and conflicts were resolved by manual correction. As a result, 381 skills, 185 knowledge concepts, and 5 transversal skills were labelled as green.

[20] The identified green *skills* most often pertain to the 'information skills' and the 'communication, collaboration and creativity' domains; while the identified green *knowledge* concepts most frequently concern knowledge in STEM-related domains (engineering, manufacturing, construction; natural sciences, mathematics, statistics) (European Commission, 2022*a*).

[21] While there are around 436 ISCO 4-digit occupations, ESCO describes more than 3000 occupations. In comparison, there are around 1000 occupations in the O*NET-SOC classification. Recently, an ESCO-O*NET crosswalk has been developed (European Commission, 2022*b*).

done based on O*NET. While the O*NET methodology refers to *green tasks*, and the ESCO-methodology to *green skills,* and in theory these concepts are different, in practice, the difference seems small or inexistent since ESCO skills are often formulated as tasks and employ action verbs. It is therefore interesting to try to translate the same approach used in the ONET-based methodology to the European level, despite the limitation in the scope of the data mentioned above.

It is important to note that the methodology which is presented in this paper as the "ESCO-based methodology", is only making use of information included in ESCO. It is not explicitly endorsed by the European Commission's ESCO team, and should by no means be interpreted as being the only possible methodology to use information in ESCO to define green jobs. Hence, any reference to an ESCO-based methodology in this paper refers to the specific ESCO-based methodology used in this paper, which is only one of the many possible ways to use information in ESCO to make relevant inferences with regard to green jobs. The choice of methodology is the sole responsibility of the authors of this paper and by no means prejudges the European Commission's institutional opinion on how to best define green jobs. At the 3-digit level of ISCO-08, at which European labour market data are available, 130 different occupational groups can be discerned. Following this methodology, the obtained score for these 130 occupations ranges from 0 to 57.9%, with a median of 2.8%. In the binary definition, 15 occupations at ISCO 3-digit level have a score greater than 10% (Table 2). Together, these occupations comprise 7.1% of employment in the EU27 in 2022 (the latest year of available data).[22] A continuous approach would reduce this figure to 4.0%.

Hence, compared to the methodology using O*NET-based information, this methodology identifies higher proportions of green tasks at the occupation-level and a wider set of occupations as having at least 10% green skill content. A major difference is that it leads to higher green task scores for occupations in agriculture as compared to O*NET methodology. In addition, for instance, it generates different results for managerial categories: while using ESCO-based information, only managers in agriculture, food and accommodation are flagged as green, broader management categories are flagged as green when using O*NET. As will be discussed later, the difference between ESCO and O*NET-based results has important implications for the further characterisation of green jobs.

Table 1 Comparison of the ESCO- and O*NET-based green tagging methodology

	ESCO	O*NET
Occupational classification	ISCO-08	US SOC2010
Granularity	ISCO 4-digit[23]	SOC 8-digit
Date of green classification	2022	2009
Classification method	Combination of human labelling and machine learning techniques	Human labelling
Occupations at ISCO 3-D level with green intensity >10%[24]	15 7.1% of EU27 employment	11 7.5% of EU27 employment

While the number of occupations tagged as green is of fairly similar magnitude when using ESCO and O*NET information respectively, the overlap is surprisingly thin and consists of only four occupational categories: engineering professionals, life science professionals, life science technicians and refuse

[22] In comparison, 109 occupational groups at the ISCO-3D level have a green intensity score above 0. With a binary definition defining all occupations with a non-zero (ESCO-based) green intensity score as green occupations, these would cover 83% of employment in the EU. Such a wide definition thus seems less suitable.

[23] In fact, ESCO is more granular than ISCO, and thus goes beyond 4 digits. However, for the purpose of this exercise, the ISCO classification is used, which goes up to 4 digits maximum.

[24] In the case of ESCO, these are derived by working with information available in ESCO and applying the same approach used in O*NET-based approaches. It is important to keep in mind that ESCO does not directly label nor define jobs as green. Moreover, skills and knowledge were assigned to occupations without any prejudice on measuring the effects of the twin transition.

workers (see Table 2). One could consider these four occupations as being "*green*" with higher certainty or consensus. At 2.5%, however, they represent only a small fraction of employment in the EU27 in 2022, of similar magnitude as the proportion of green jobs identified based on the EGSS methodology.

Table 2 Occupations with a green skill intensity >10% in ESCO and O*NET

ISCO 3-Digit Code		ESCO	O*NET
>10% in both classifications			
213	Life science professionals	22.9	34.3
214	Engineering professionals (excluding electrotechnology)	12.6	30.8
314	Life science technicians and related associate professionals	16.7	17.6
961	Refuse workers	47.3	38.7
>10% only in ESCO			
131	Production managers in agriculture, forestry and fisheries	14.4	1.8
141	Hotel and restaurant managers	10.4	0.0
225	Veterinarians	10.4	0.0
313	Process control technicians	17.2	1.3
611	Market gardeners and crop growers	32.3	0.0
613	Mixed crop and animal producers	35.2	0.0
621	Forestry and related workers	57.9	0.0
631	Subsistence crop farmers	32.3	0.0
633	Subsistence mixed crop and livestock farmers	35.2	0.0
713	Painters, building structure cleaners and related trades workers	14.0	0.0
*>10% only in O*NET*			
112	Managing directors and chief executives	3.2	15.8
122	Sales, marketing and development managers	2.5	22.2
132	Manufacturing, mining, construction, and distribution managers	5.1	22.9
211	Physical and earth science professionals	7.5	11.2
216	Architects, planners, surveyors and designers	4.3	11.9
712	Building finishers and related trades workers	9.8	10.5
931	Mining and construction labourers	5.5	12.1

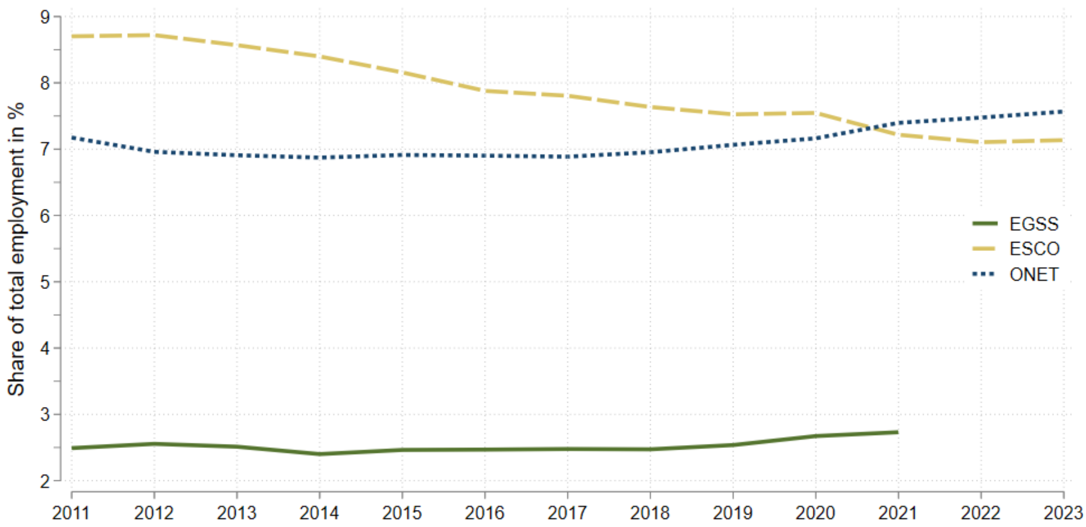
Note: The table shows the share of green skills in total skills (the "green intensity score") of the respective occupation by ISCO 3-digit occupational category from the ESCO classification and the O*NET classification (from Bluedorn et al (2022)) for occupations with a green skill intensity score larger than 10% in at least one of the classifications.

3. DYNAMICS IN GREEN JOBS OVER TIME IN THE EU

While distinct in their levels, the three indicators also present different dynamics. The EGSS-based indicator (solid dark green line) considers a relatively low proportion of the workforce to be in green employment (less than 3%) but shows a rising trend as of 2018 (Figure 1). The O*NET-based indicator (dotted blue line) considers around 7% of employment as green, and shows a weak upward trend in the most recent years. The ESCO-based indicator (dashed beige line) currently hovers around 7%, close to the O*NET based indicator, but it presents a decline over the last decade and a stagnation in the most recent years. A major reason for this is the inclusion of agricultural jobs in the indicator, with agricultural employment consistently contracting over time. If agricultural jobs are excluded, the level drops to a bit below 5% of total EU employment and shows relative stability over the considered time period. Table A.1 in Annex presents available time series data by EU Member States.

Hence, remarkably, observed growth in green jobs is considerably weaker than one would have expected ex ante, in view of the significant adoption of green policies in recent years.[25] The low growth dynamics in green employment could relate to measurement error due to the high level of aggregation of the data, forced by data limitations, which might obfuscate certain trends. The analysis in this paper also finds that a continuous approach to measuring green jobs in the task-based approach would lead to a lower estimate of the incidence of green jobs (see above), which is consistent with Elliott et al. (2022)'s conclusion. The low share of green jobs is not necessarily an impediment for the green transition since occupations that are relatively small in terms of employment shares can be crucial to design and implement far-reaching structural transformations.[26] Moreover, the everyday business decisions of people (also of those that do not have green tasks formally enshrined in their job description) may also play a role in advancing the green transition (e.g. regarding the inputs that they buy).

Figure 1 Share of green jobs in the EU27, 2011-23



Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

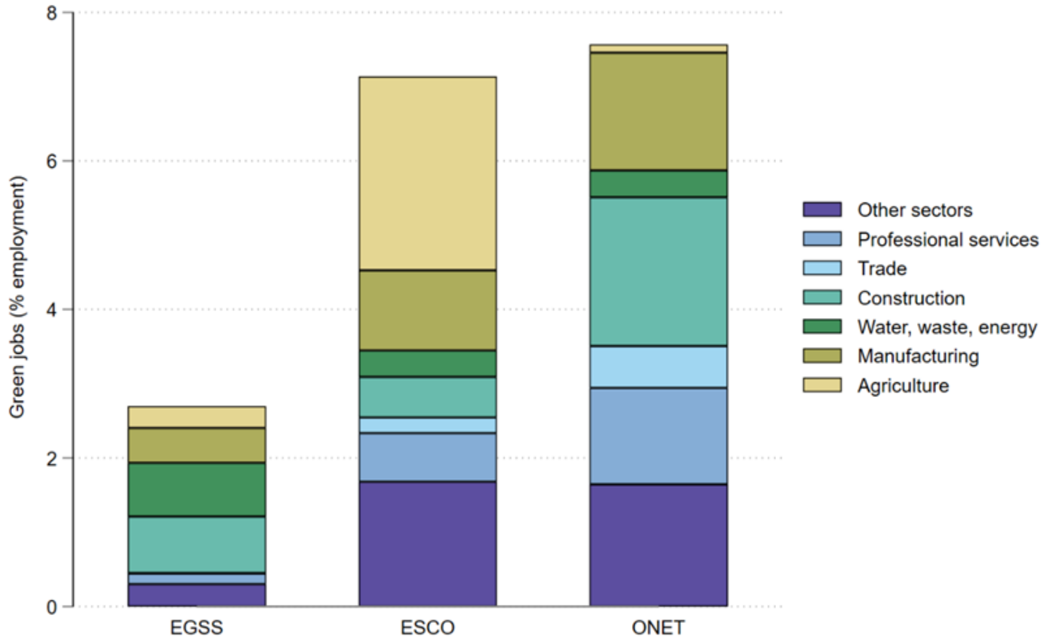
4. SECTORAL CHARACTERISTICS

The three approaches have different implications for the sectoral distribution of green jobs (Figure 2). Notably, the EGSS-based methodology suggests more than 60% of green jobs are in manufacturing, water and waste management, and construction. Following the ESCO-based methodology, agriculture and manufacturing become central in green employment (together making up more than half of green jobs). 'Other sectors' also play a significant role, particularly driven by food & accommodation, administrative and support service activities, and public administration. Following the O*NET-based methodology, 65% of green jobs are in manufacturing, construction, and professional services.

[25] Using the continuous approach would lead to lower estimates for the proportion of green jobs; but the trends would still be similar.

[26] https://www.cedefop.europa.eu/en/news/circular-economy-step-skill-needs-and-importance-thyroid-occupations.

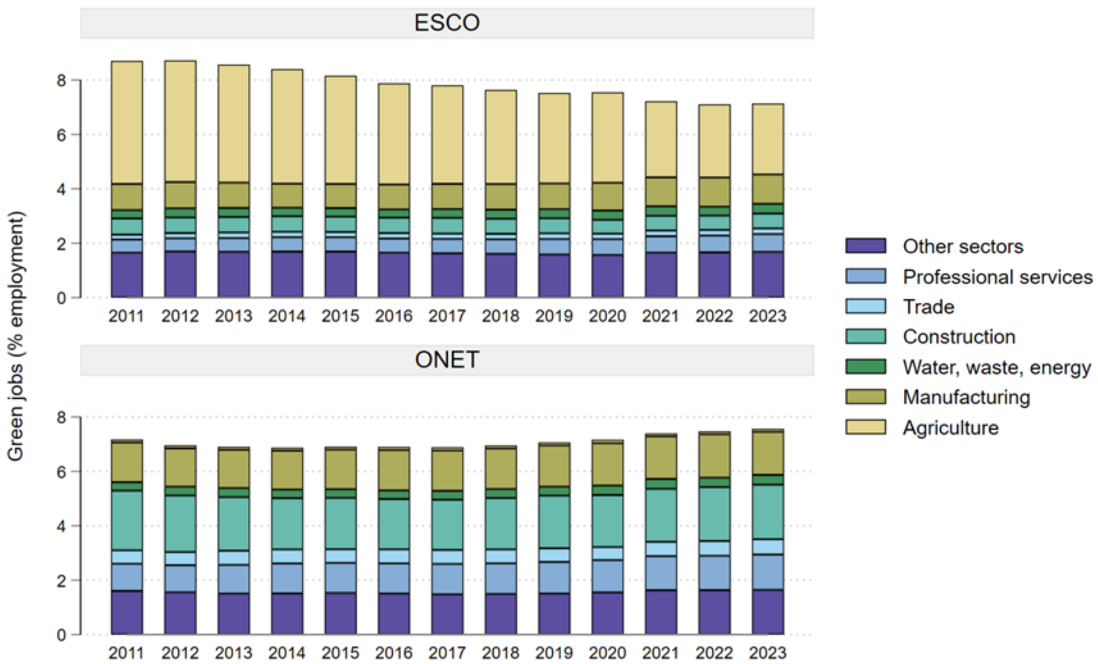
Figure 2 Sectoral distribution of green jobs, EU27, latest data available



Note: EGSS EU aggregate is calculated as simple sum of employment by member states (based on Eurostat variable env_ac_egss1). Latest year available for EGSS: 2021, latest year available for ESCO, O*NET: 2023.

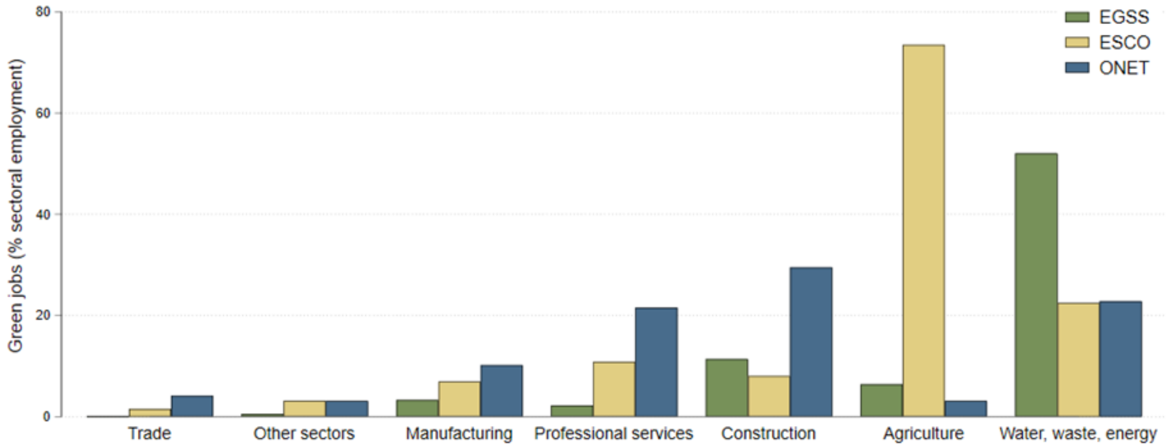
Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

Figure 3 Changes in sectoral composition of green jobs, EU27, 2011-2023



Source: Authors' own calculations based on LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

Figure 4 Share of green jobs in sectoral employment, EU27, latest year available



Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

In other words, while the ESCO-based methodology underlines the green character of jobs in agriculture, the O*NET-based methodology puts more emphasis on green service jobs, covering around 50% of all green jobs. This partially explains why green jobs are declining according to the ESCO-based methodology (as agricultural jobs are declining in the EU), while they are modestly growing according to the O*NET methodology (in line with observed growth in service jobs) (see Figure 3). The implementation of this methodology on ESCO data suggests a decreasing trend in green jobs within the agricultural sector, and minor decreases in construction, while green jobs are modestly growing in manufacturing, water, waste, energy, trade, and professional services. Hence, overall, the dynamics in this indicator are strongly driven by the agricultural sector – other than that, the sectoral composition is changing very slowly. The O*NET-based methodology suggests modest increases in green jobs in the same sectors as the ESCO-based methodology (manufacturing, water, waste, energy, trade and professional services). The different green job profiles are also reflected in the respective skills distributions of green jobs according to the two task-based approaches (see Section 5.3).

One can also consider the share of green jobs in sectoral employment as a measure of 'greenness' of economic activities (Figure 4). The EGSS method would then identify water, waste and energy (NACE 1-digit D and E) as the overwhelmingly greenest sector. Conversely, results from the ESCO-based methodology suggest that the agricultural sector (NACE 1-digit A) is the greenest sector by far, followed by water, waste, and energy. Finally, the O*NET method would identify construction (NACE 1-digit F), water, waste and energy (NACE 1-digit D and E), and professional services (NACE 1-digit M) as the greenest sectors. These sectoral patterns are relatively similar across Member States, with a few exceptions (see Figure A.2 in Annex).

EGSS data allow for the identification of green jobs by purpose (Figure A.3 in Annex). The two main categories in this regard are environmental protection and resource management. Among the subcategories of resource management, there is one that identifies jobs in the management of energy resources. For instance, a solar panel installer would be comprised in this category. In most countries, jobs contributing to environmental protection are more numerous than jobs in resource management, even if the former remain unlikely to rise above 2% of total employment in any country. Jobs in resource management (including energy) are particularly widespread in Luxembourg, Estonia, and Finland.

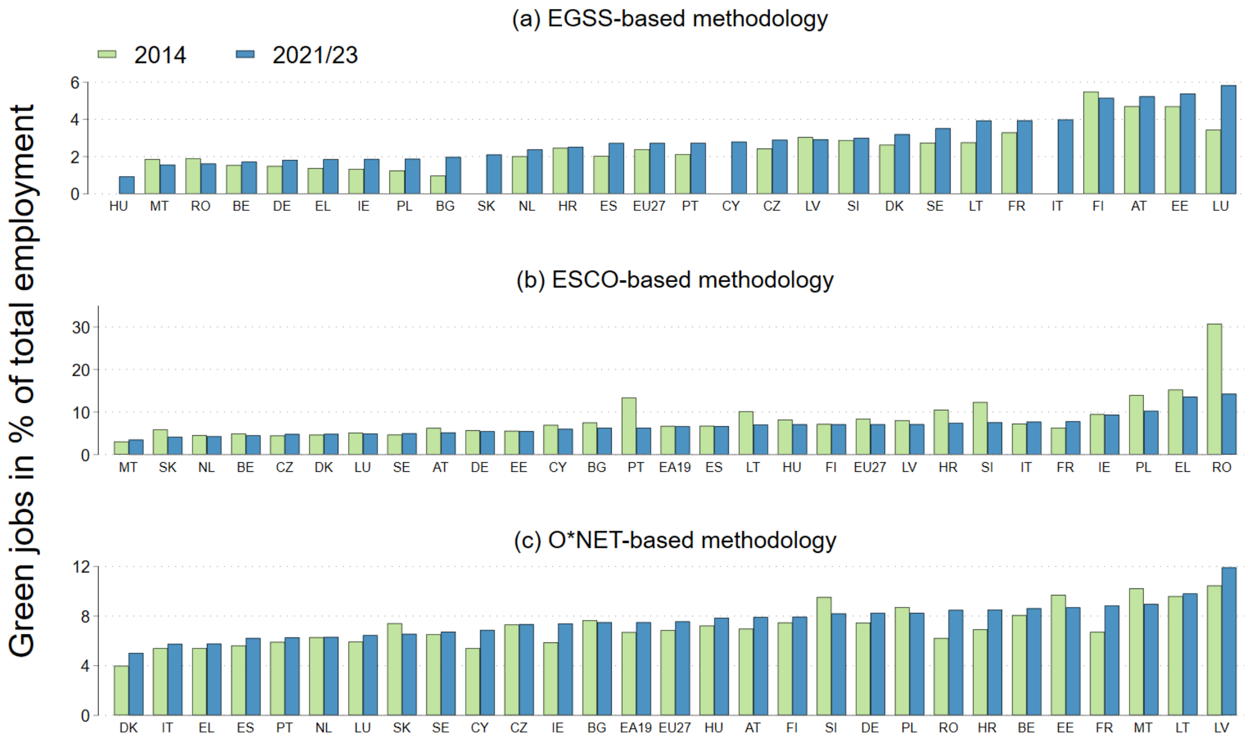
5. DISTRIBUTION OF GREEN OCCUPATIONS IN THE EU

The three methodologies have different implications for the distributional characteristics of green employment in the EU. The green occupations identified based on ESCO data and O*NET can be linked to employment data at the ISCO-08 3-digit level from the EU Labour Force Survey (EU-LFS) to examine their distribution across Member States, sectors (NACE 1-digit level), regions (NUTS-2 level), and characteristics of jobs and workers (e.g., skills requirements and qualification levels).[27] The EGSS-based definition does not allow for a direct link with LFS data, but a disaggregation is possible by Member States, sectors, and by purpose (environmental protection versus resource management, see earlier).

5.1. DISTRIBUTION ACROSS MEMBER STATES

The three methodologies lead to differences in the distribution of green jobs across EU Member States. The respective distributions are presented in Figure 5.

Figure 5 Green jobs by Member State in 2014 and latest year available



Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

In panel (a), the EGSS-based methodology suggests that the largest shares of green jobs are found in Luxembourg, Estonia, Austria, and Finland in 2021. At the other end of the spectrum are Hungary, Malta, Romania, Belgium, Germany, Greece, Poland, and Ireland. In panel (b), in contrast, the ESCO-based methodology would suggest Romania, Greece, Poland, and Ireland have a relatively high proportion of green jobs, even if Malta and Belgium remain among tail performers.

It is clear that the sectoral composition of employment influences significantly the distribution of certain occupational categories, and thus also of green jobs as identified through task-based approaches across countries in the EU. For instance, in Romania, Greece, and Poland, this is likely related to the high share of

[27] Combinations of breakdowns are usually not available due to data protection regulations. Further work could look into additional dimensions of worker characteristics such as gender, age, contract type etc.

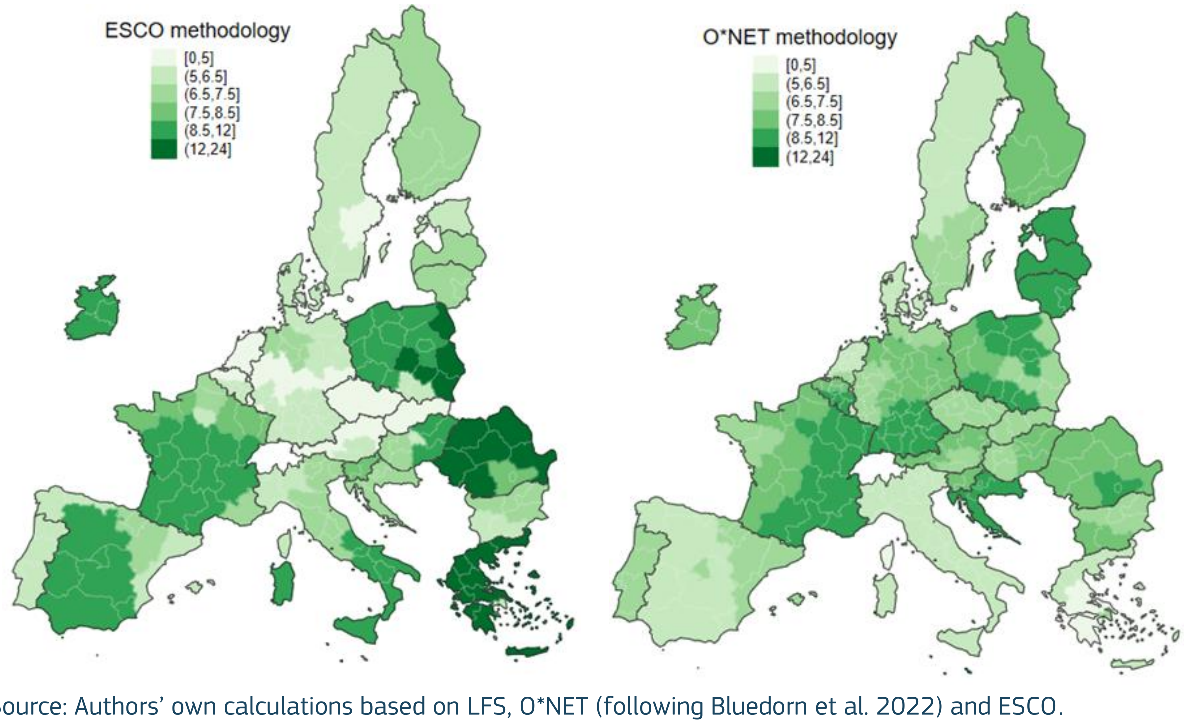
employment in agriculture. In Ireland, the agricultural sector is also still significant (at almost 5% of employment); but in contrast with other countries, all (100%) jobs in the Irish agricultural sector are considered green.[28] The decline in ESCO-based green employment over time is visible in most Member States, with the largest declines observed in countries which had a large agricultural sector in 2011 (e.g. Portugal, Romania).

The O*NET-based indicator in panel (c) again shows a different picture, with Malta, Belgium, and Hungary performing relatively well, while Greece is among the laggards. In other words, the three indicators paint a fairly different picture of the cross-country distribution of green jobs. This lack of robustness across methodologies should be taken into account and warrant caution in the interpretation of green job data.

5.2. DISTRIBUTION OF GREEN JOBS BY REGION

Figure 6 presents the distribution of green jobs across EU regions in 2021, following the ESCO- and the O*NET-based methodologies.[29] The EGSS indicator as yet does not allow for regional disaggregation. Following the ESCO-based methodology, the highest regional concentration of green jobs is observed in Southern European countries (e.g. Greece, Italy, Spain, Croatia), Eastern European countries (e.g. Poland and Romania), Ireland and a few regions in France (Figure 6), reflecting to some extent the regional distribution of the agricultural sector, which is the sector with the highest proportions of green jobs in all Member States (Figure A.2 in Annex). In the O*NET methodology, the regions with the strongest concentration of green jobs are found in the Baltic countries, southern regions of Germany and France, Slovenia as well as a few regions in Romania and Poland.

Figure 6 Share of green jobs by region, 2023



Source: Authors' own calculations based on LFS, O*NET (following Bluedorn et al. 2022) and ESCO.

[28] For comparison, in the Netherlands, only 38% of jobs in the agricultural sector would qualify as green under the ESCO-based methodology.

[29] An extensive discussion of the regional distribution of green jobs using a different, but related O*NET-based approach is also provided by OECD (2023).

5.3. DISTRIBUTION OF GREEN JOBS BY WORKER CHARACTERISTICS

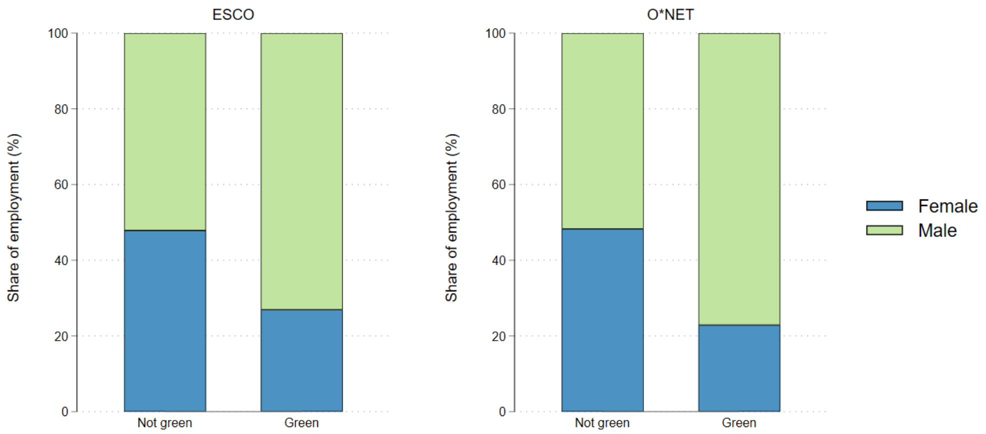
The skills profiles of green jobs vary by the different definitions of green jobs. LFS data allow for the consideration of two skills dimensions. On the one hand, one can look at the qualifications held by workers currently occupying a job, where typically three education levels are discerned (no secondary qualification, secondary qualification, or tertiary qualification). On the other hand, one can look at the skills requirements of those jobs, which can be derived in broad terms from their ISCO classification. In the latter case, occupations in ISCO-1D categories 9 are considered as low-skilled, those in categories 4-8 as medium-skilled, and those in categories 1-3 as high-skilled, in line with standard practices in the literature (e.g. ILO, 2007). As the analysis shows, in many cases there is no direct correspondence between the qualification level of workers and the skills requirements of their job. This is in part due to the very rough approximation of the job skills requirements (at the ISCO 1D-level), but also because workers' qualification levels do not always precisely reflect their job-related skills or responsibilities. A contributing reason is that the classification does not account for changes over time in skills requirements within occupations. Moreover, workers may also accumulate skills through job experience, allowing them to take up jobs with higher skills requirements than they would formally have qualifications for. Managers are invariably classified as 'high-skilled' as managerial responsibilities are considered to require a high qualification level. However, this does not always reflect jobholders' academic qualifications. For example, hotel and restaurant managers (ISCO-3D code 141) are classified as 'high-skilled', while only 25% of workers in this occupation held a tertiary degree in 2023 in the EU27.

Figure 7 Distribution green jobs by workers' qualifications and job skill requirements, EU27, 2023

Note: Qualifications are classified by ISCED category as follows: ISCED 0-2: low; ISCED 3-4: medium; ISCED 5-8: high. Occupations in ISCO-1D categories 9 are considered as low-skilled, those in categories 8-4 as medium-skilled, and those in categories 1-3 as high-skilled, in line with standard practice (e.g. ILO, 2007). Observations with missing data on ISCO or ISCED levels are dropped from the analysis.

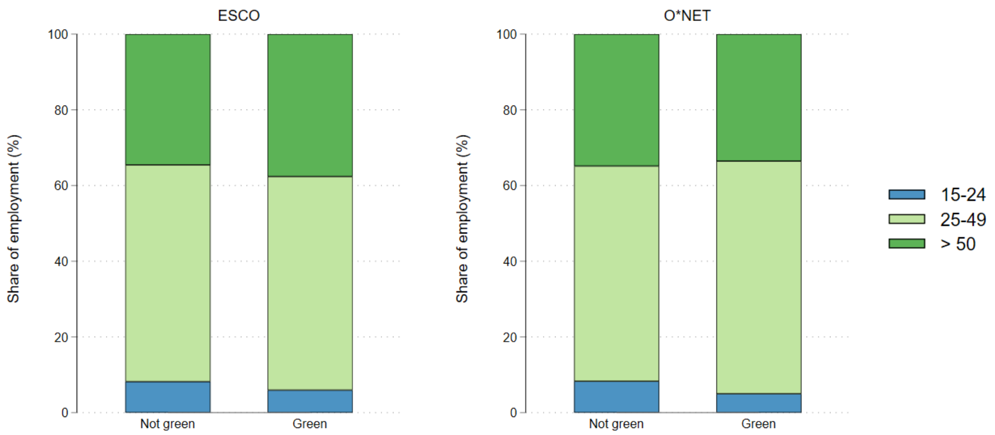
Source: Authors' own calculations based on LFS, ESCO, ONET (following Bluedorn et al., 2022).

Figure 8 Distribution green jobs by workers' gender, EU27, 2023



Source: Authors' own calculations based on LFS, ESCO, ONET (following Bluedorn et al., 2022).

Figure 9 Distribution green jobs by workers' age, EU27, 2023



Source: Authors' own calculations based on LFS, ESCO, ONET (following Bluedorn et al., 2022).

When looking at qualification levels of workers currently working in green jobs, it is clear that workers in green jobs according to the O*NET-based methodology used in this paper[30] are generally more likely to have a tertiary qualification than those in non-green jobs,[31] or those who work in green jobs according to the ESCO-based methodology (Figure 7 a). Conversely, according to the ESCO-based methodology, workers in green jobs seem to be more likely to be lower qualified as compared to those in non-green jobs or those in O*NET green jobs. A contributing factor is the important contribution of agricultural jobs among ESCO green jobs, where lower qualified workers are strongly overrepresented; while O*NET green jobs focus on more technical profiles, and are more likely to be categorised as managerial and professional jobs (ISCO 1-D categories 1 and 2). The O*NET skills distribution is more in line with earlier literature on the topic,

[30] For instance, O*NET-based approaches that do not restrict themselves to jobs that have a non-zero green task content, but that for instance also include broader jobs for which demand is expected to grow as a result of the green transition, may lead to different conclusions regarding skills composition.

[31] It is possible that the crosswalk from the SOC-based ONET to ISCO categories, which is needed to apply the ONET-based approach to EU data, induces a high-skills bias, as ISCO groups 1-5 (which comprise high-skilled and some medium-skilled occupational groups) can be matched more easily with the corresponding SOC-groups (Oshafi, work in progress).

which has suggested that green jobs are likely to require higher skills, reflecting the relevance of engineering and science professions for the green transition.[32]

When considering job skills requirements, a similar pattern appears (Figure 7 b). Here, the orientation towards high skilled jobs in the O*NET green job definition is even more pronounced, with around 70% of green jobs requiring a high level of skills. ESCO green jobs still seem to have quite similar skills requirements than non-green jobs (with a slight overrepresentation of low-skilled jobs). Irrespective of the methodology used, medium-skilled jobs seem to occupy a smaller share of green jobs than of non-green jobs. As shown by Figure A.4 in the Annex, the share of green jobs with high skills requirements is rising over time in both task-based approaches.

The ESCO and O*NET indicators reveal a similar gender pattern: workers in green jobs are more likely to be male than the average worker (Figure 8). This gender pattern has been observed in other studies as well. The age distribution of workers in green jobs is relatively similar to the age distribution of the average worker; although green jobs are somewhat less likely to be held by young workers (age group 15-24) (Figure 9). In that sense, the demographic characteristics of green jobs are relatively similar to those of brown jobs (see Vandeplas et al., 2022).

6. DISCUSSION AND WAY FORWARD

Overall, the analysis in this paper suggests that the prevalence, the evolution, and the distribution of green jobs are strongly determined by how green jobs are defined and measured. The paper illustrates this by comparing three different approaches that provide cross-country comparable results.

The first method is based on environmental accounts data and is helpful in that it takes into account process and outcomes when defining green jobs. At the same time, it is less helpful when it comes to socioeconomic analysis, which means it remains useful to explore alternative methodologies to improve our understanding of the characteristics of green jobs and the workers who occupy these.

The other two methods reflect task-based approaches. These are useful to get a better understanding of the characteristics of green jobs at the micro-level, but also present a number of important drawbacks.

First, the highest level of detail at which Eurostat makes available employment data across all EU countries is ISCO 3-D. This results in a fairly coarse classification of occupations, which is a major drawback for the analysis and introduces considerable measurement error (see Vona (2021) for an extensive discussion). For instance, the task-based approaches would not allow for a distinction between engineers in the renewable energy and the fossil-based energy sectors. In other words, the aim of the analysis, and the possible policy focus, would thus be important elements in selecting the most appropriate data source.

An important advantage of the ESCO-based methodology applied in this paper for applications to European labour market data is that, in contrast to the O*NET methodology, it does not require a crosswalk for its integration with European labour market data, which in the case of the O*NET indicator results in a significant loss of information. Therefore, further exploring the wide opportunities offered by the rich information in the ESCO-database would be useful for future research. For instance, an interesting application would be to combine ESCO information on green skills with online vacancy information provided by Skills-OVATE to track the most recent developments in green job creation.[33] At the same time, this does not resolve the problem that LFS data are only available at the ISCO-3D level of aggregation, which is not sufficient to identify green jobs in a satisfactory way. Based on results by OECD (2023), It is not clear that a disaggregation to ISCO-4D, which is only slightly more granular, would substantially improve the results.

A further shortcoming of the task-based approaches presented in this paper is that they are static in the sense that they fix the task content of jobs at the moment that occupations are described. While this is

[32] See Vandeplas et al. (2022) for a brief overview.

[33] https://www.cedefop.europa.eu/en/tools/skills-online-vacancies

an attractive feature in terms of transparency and simplicity, it also means that these approaches would only pick up greening of employment through a shift between occupations, towards greener occupations. They do not pick up greening of task content *within* an occupation, which nevertheless has been identified as an important driver of changes in green task content. Moreover, the green tagging has been carried out by experts who have made assumptions on skills needed for or the task content of specific jobs – but this is clearly only an approximation of tasks effectively carried out or skills effectively owned by workers in these jobs (cfr. Handel, 2020).

The ESCO definition of green skills as skills 'aimed at reducing the impact of human activities on the environment' is based on a broad concept of a green economy, which includes aspects such as the protection of biodiversity and natural resources. For research that focuses more narrowly on climate neutrality, a narrower definition of limiting and reducing pollution can be more appropriate.

Next, an important caveat is that green tasks also occur for jobs that are not traditionally considered as green. For example, restaurant managers or painters are rarely considered green jobs. Yet, they have a range of tasks that relate to waste management and compliance with environmental regulations and represent a significant proportion of their overall tasks.

This also means that jobs involving green tasks may often be found in highly polluting activities, which are most likely to be subject to environmental regulation and therefore require job holders to take action to comply with those regulations and reduce the activities' impact on the environment. The sectors identified as those with the highest greenhouse gas emissions by Vandeplas et al. (2022), notably agriculture, mining, and manufacturing, make up for 23%-53% of green jobs in the EU in 2021/22, depending on the methodology considered.[34] The agricultural sector features particularly prominently among green jobs when using the ESCO-based methodology.[35] IMF (2022) and Scholl et al. (2023) address the overlap between green and brown (polluting) jobs by defining green jobs as those with a strictly positive green task intensity *and* a zero pollution intensity. In the analysis in this paper, the overlap has not been addressed, implying that several of the identified green jobs could equally qualify as brown jobs.

Finally, it should be kept in mind that none of these data sources provide clear messages on whether *more green jobs* would necessarily coincide with a *greener economy* (e.g. Bruvoll et al. 2012:27) or if stricter environmental regulation would trigger a temporary or rather a sustained increase in green job creation (e.g. Vona et al. 2018). For instance, a higher level of employment in waste treatment can reflect higher policy attention given to recycling. It can however also reflect higher waste production and/or a less efficient organisation of work in the waste treatment sector. In future work, the nexus between green and brown jobs could be further examined to further investigate how to best address the overlap between these two categories.

The European Commission is working on improving the statistical capacity and the understanding of methodological challenges to facilitate the identification of green jobs going forward. Major efforts are going on in this regard as part of the "GreenJobs" project, for which results will be available soon.

[34] EGSS: 29%; ESCO: 53%; O*NET: 23%.

[35] Two out of three subsectors in agriculture (A01-Crop and animal production and A03-Fishing and aquaculture) were identified as 'brown' sectors in Vandeplas et al. (2022) based on a ranking of subsectors on greenhouse gas emissions per worker. If one would have alternatively looked at CO_2 emissions alone (rather than at all greenhouse gases), only 1 subsector in agriculture (A03) would have been flagged as brown. Both approaches are valid. While Vona et al. (2018) consider a group of greenhouse gases, Bluedorn et al. (2022) also consider an indicator solely based on CO_2 emissions.

7. CONCLUSION

The analysis in this paper illustrates three different methodologies to measure green jobs in EU labour market data and assess the volume, the dynamics and the distribution of green jobs in the EU.

The EGSS-based method puts the current proportion of green jobs in total employment at almost 3%; the ESCO- and O*NET-based methods put it around 7%. While the EGSS- and O*NET-based methodologies show a slow increase in the proportion of green jobs; the ESCO-based methodology shows a decline over time, driven by the decline in jobs in the agricultural sector. The low growth dynamics in green employment could relate to measurement error or other data limitations. At the same time, a low share of green jobs would not necessarily be an impediment for the green transition since occupations that are relatively small in terms of employment shares can be crucial to design and implement far-reaching structural transformations. Moreover, the everyday business decisions of people (also of those that do not have green tasks formally enshrined in their job description) may also play a role in advancing the green transition (e.g. regarding the inputs that they buy).

With respect to the sectoral distribution, the EGSS-based methodology identifies water, waste and energy as the greenest sector; the ESCO-and O*NET-based methodologies identify the agricultural and the construction sector respectively as the greenest sectors. When considering overall employment, thus taking into account the relative employment shares of each sector, the largest proportion of green jobs belong to sectors such as agriculture, industry, and construction. The agricultural sector is particularly well represented among green jobs when using the ESCO-based methodology. At the same time, the task-based approaches also identify a significant and growing proportion of green jobs in services.

The differences in the sectoral distribution of green jobs are reflected in the variation in the geographical and skills distribution of green jobs across the three methodologies. While still representing a minor proportion of green jobs overall, low-skilled jobs take up a larger proportion of green jobs than of non-green jobs according to the ESCO-based methodology; while high-skilled jobs are strongly overrepresented among green jobs when using the O*NET-based methodology. Both task-based methodologies suggest that green jobs are more likely to be taken up by men than by women, while the age profile of workers in green jobs is quite similar to the age profile of workers in non-green jobs.

An important insight from the analysis is that the considered methodologies produce diverging results when it comes to the geographical, sectoral, ands skills distribution of green jobs[36]. This means that any findings on the dynamics, job and worker characteristics of green occupations critically hinge on the approach chosen to identify green jobs, and has to be seen in light of that. The differences in results across the different methodologies relate to differences in the conceptual approach to green tagging in the underlying methodologies, but also to some extent to measurement errors, including those resulting from data constraints and from assumptions needed for crosswalking across multiple levels of data granularity.

While the O*NET-based methodology identifies in particular managerial and professional occupations as green, the ESCO-based methodology identifies several agriculture-related jobs as green that are not identified as green in the O*NET-based methodology presented in this paper. Accordingly, green jobs identified by the O*NET methodology used in this paper have higher skills requirements than those identified using ESCO information. The rising trend in green jobs is somewhat more significant when focusing on high-skilled green jobs.

The analysis in this paper demonstrates that the high level of aggregation of the labour market data provided by Eurostat is an important constraint for the identification of green occupations using task-based approaches. This constraint applies equally to the ESCO and the O*NET methodologies. Using occupational data at the ISCO 4-digit level (or even at a more granular level) could increase confidence that what is captured by the data are truly green jobs, even if work by OECD (2023) and internal analysis at the European Commission suggest that the main results of ISCO-3 digit-based approaches would carry over to ISCO-4-digit based approaches.

[36] See for instance the differences in ranking order between countries; or the relatively low correlation between regional employment shares according to the two indicators.

Altogether, the diverging approaches to define green jobs call for further reflection and agreement regarding the criteria to distinguish green jobs from white or brown jobs. Based on the analysis in this paper, it seems that for the time being the EGSS data probably provide the best measure of green jobs in cross-country and regularly available data for the EU, with the main drawbacks being that they become available with a more significant time lag than the LFS data; and that they cannot be linked to regional, job, or worker characteristics in the same way as the task-based approaches. At the same time, given the constraints of the EGSS data in terms of opportunities for socio-economic analysis, it still seems useful to consider other approaches, including task-based ones, to get at richer insights, while checking the robustness of results across different methodologies.

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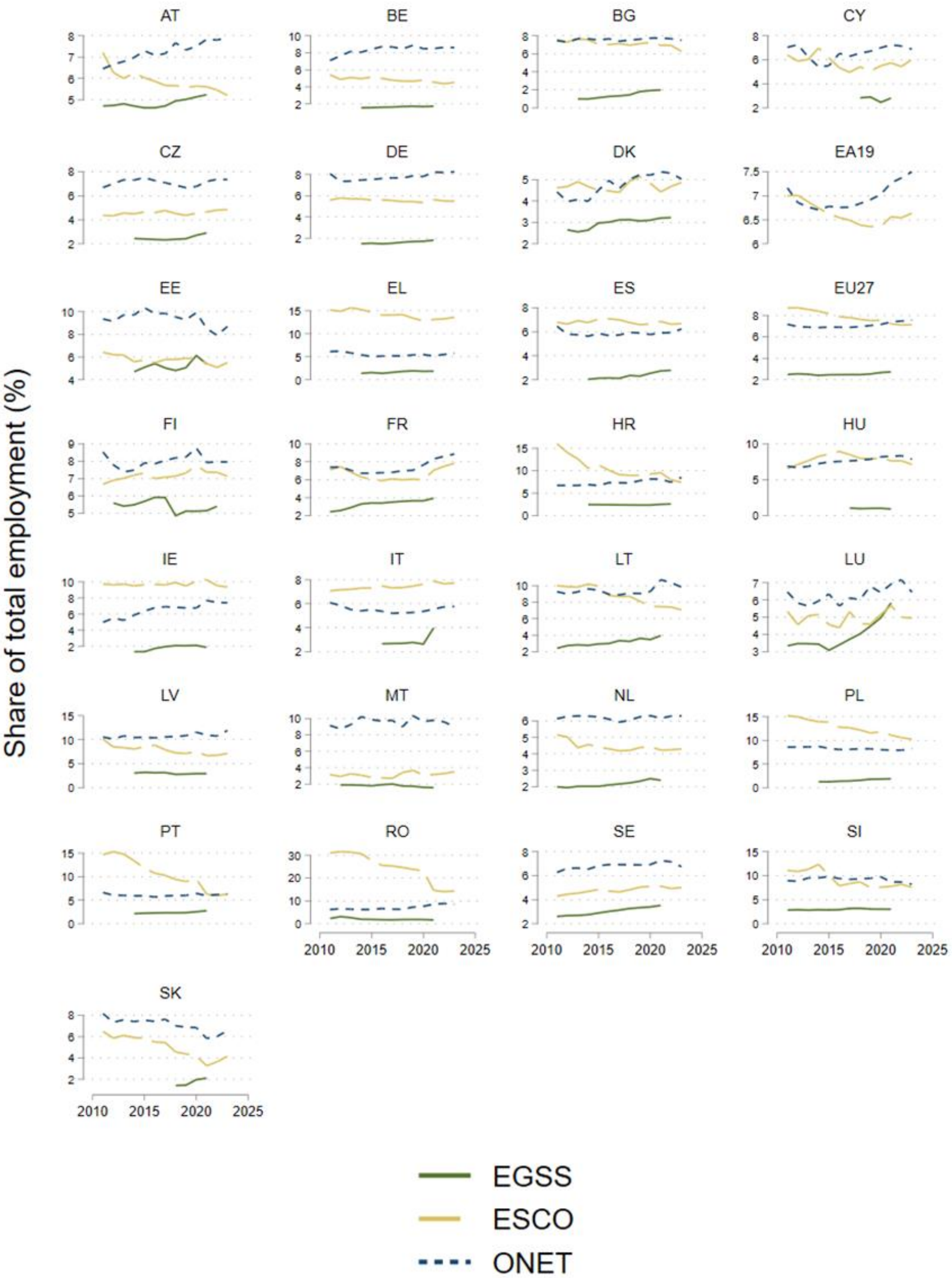
ANNEX

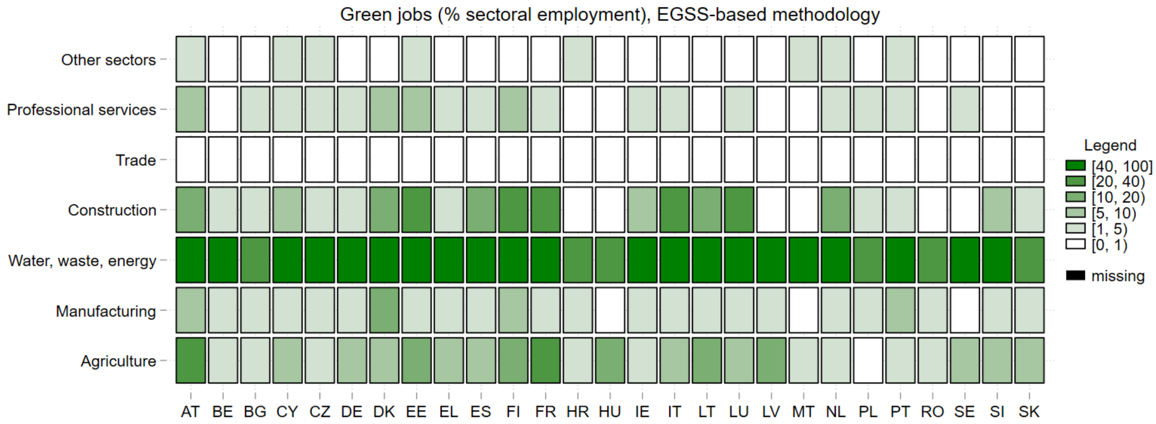
Figure A.1 Share of green jobs by EU Member State, 2011-2022, different methodologies



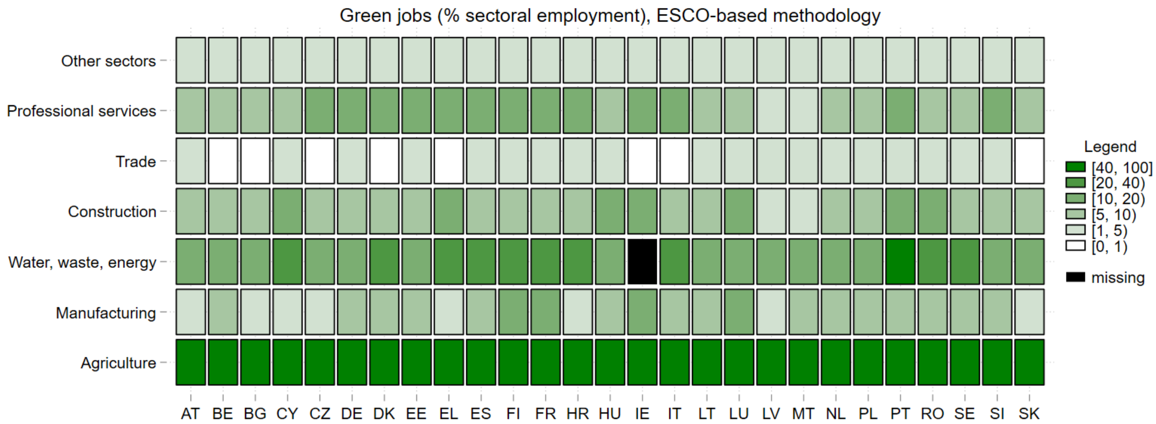
Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO

Figure A.2 Proportion of green jobs by sector and country, latest data available

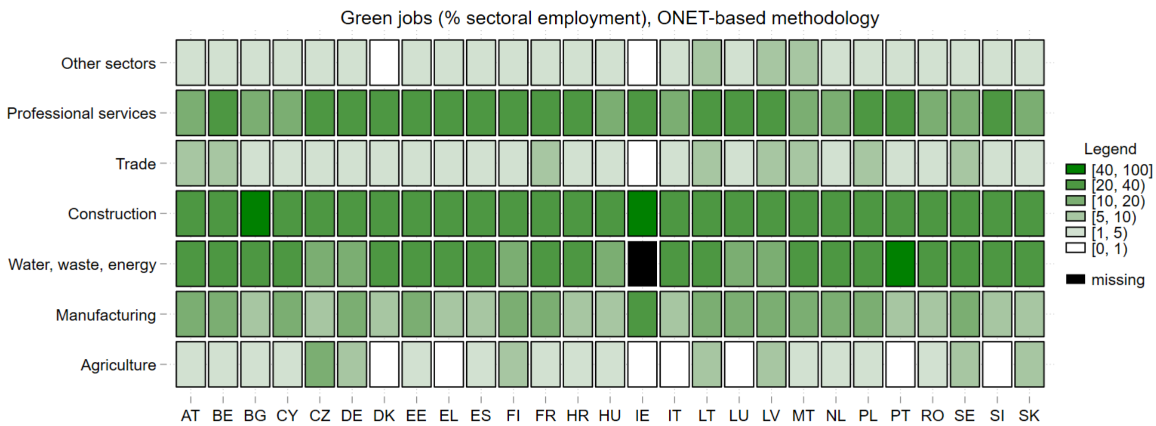
(a) EGSS-based methodology



(b) ESCO-based methodology



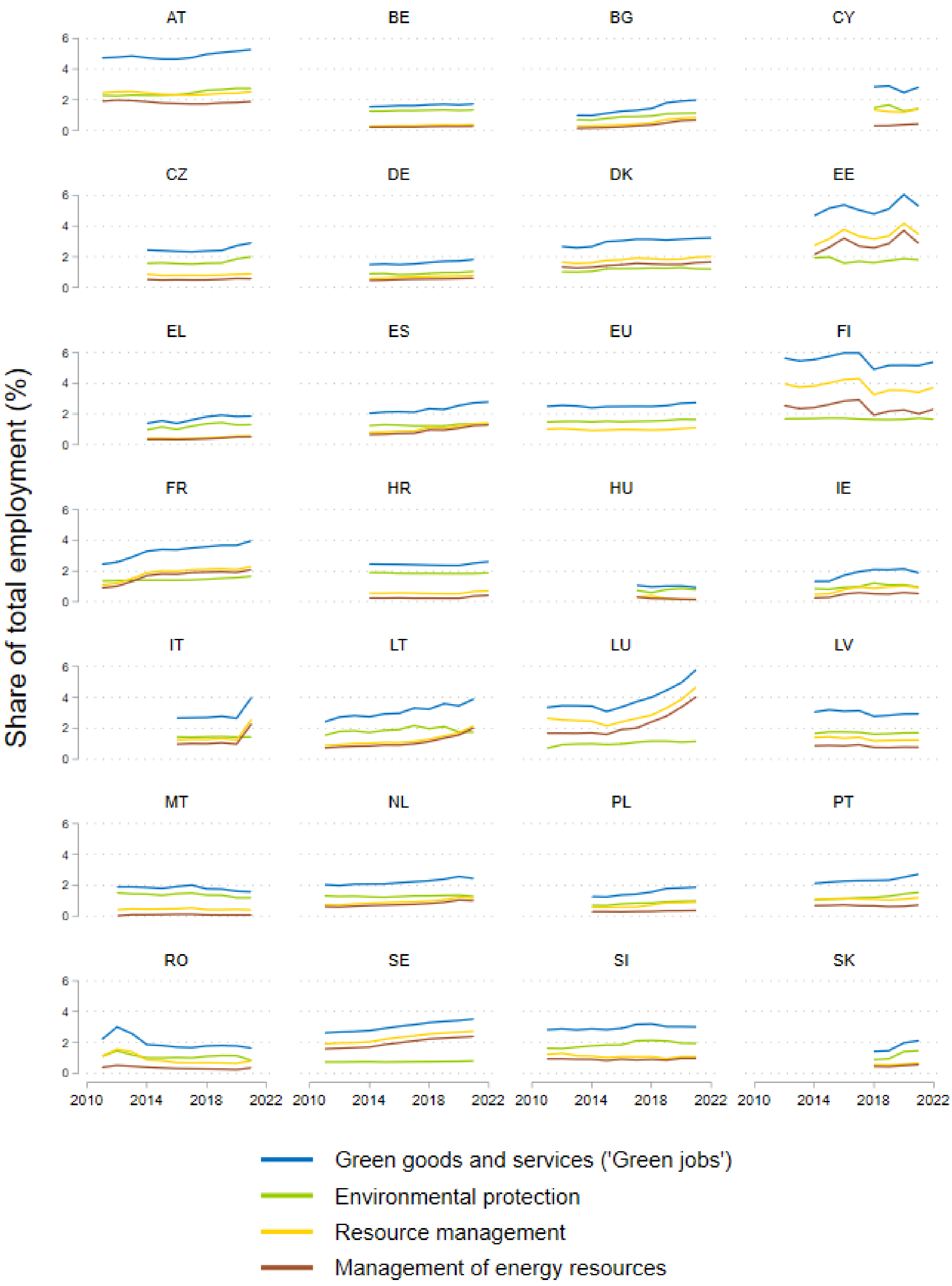
(c) O*NET-based methodology



Note: Latest year available for EGSS: 2021, latest year available for ESCO, O*NET: 2023.

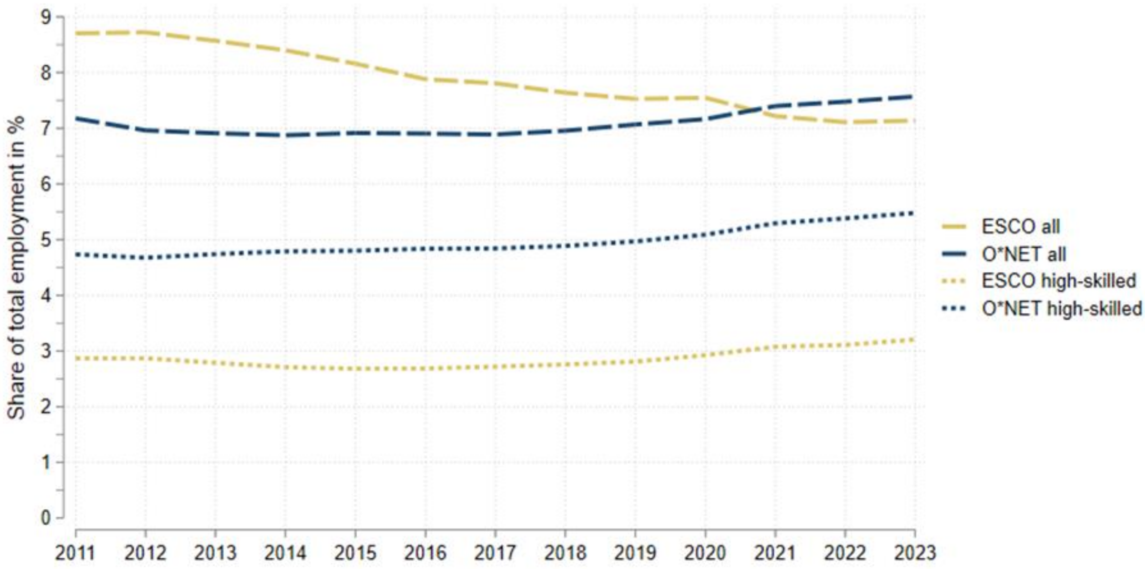
Source: Authors' own calculations based on EGSS, LFS, O*NET (following Bluedorn et al. 2022) and ESCO

Figure A.3 Dynamics of green jobs (EGSS methodology) by purpose



Source: Authors' own calculations based on EGSS

Figure A.4 Evolution of high-skilled green jobs, task-based approaches, 2011-22, EU27



Source: Authors' own calculations based on LFS, O*NET (following Bluedorn et al. 2022) and ESCO

Table A.1: Overview of green task intensity scores by ISCO 3-digit occupations

ISCO 3-Digit Code		ESCO Greenness Indicator	O*NET Greenness Indicator	IMF Pollution Intensity
011	Commissioned armed forces officers	0.28		
021	Non-commissioned armed forces officers	0.00		
031	Armed forces occupations, other ranks	0.56		
111	Legislators and senior officials	0.18	0.00	0.00
112	Managing directors and chief executives	3.23	15.80	0.00
121	Business services and administration managers	5.19	0.00	0.00
122	Sales, marketing and development managers	2.51	22.20	0.00
131	Production managers in agriculture, forestry and fisheries	14.42	1.80	0.00
132	Manufacturing, mining, construction, and distribution managers	5.08	22.90	0.00
133	Information and communications technology service managers	0.00	0.00	0.00
134	Professional services managers	3.13	0.00	0.00
141	Hotel and restaurant managers	10.49	0.00	0.00
142	Retail and wholesale trade managers	3.46	0.00	0.00
143	Other services managers	3.59	0.00	0.00
211	Physical and earth science professionals	7.50	11.20	46.90
212	Mathematicians, actuaries and statisticians	0.59	0.00	0.00
213	Life science professionals	22.92	34.30	2.30
214	Engineering professionals (excluding electrotechnology)	12.61	30.80	5.00
215	Electrotechnology engineers	5.57	9.40	0.00
216	Architects, planners, surveyors and designers	4.32	11.90	0.00
221	Medical doctors	0.00	0.00	0.00
222	Nursing and midwifery professionals	0.00	0.00	0.00
223	Traditional and complementary medicine professionals	0.59	0.00	0.00
224	Paramedical practitioners	0.00	0.00	0.00
225	Veterinarians	10.44	0.00	0.00
226	Other health professionals	2.18	0.00	0.00
231	University and higher education teachers	0.31	0.00	0.00
232	Vocational education teachers	2.08	0.00	0.00
233	Secondary education teachers	0.92	0.00	0.00
234	Primary school and early childhood teachers	0.00	0.00	0.00
235	Other teaching professionals	0.06	0.00	0.00
241	Finance professionals	1.73	5.10	0.00
242	Administration professionals	3.31	1.40	0.00
243	Sales, marketing and public relations professionals	2.50	3.90	0.00
251	Software and applications developers and analysts	0.20	0.20	0.00
252	Database and network professionals	0.00	0.00	0.00
261	Legal professionals	1.44	0.00	0.00
262	Librarians, archivists and curators	0.28	0.00	0.00
263	Social and religious professionals	0.25	2.70	0.00
264	Authors, journalists and linguists	0.00	0.40	0.00
265	Creative and performing artists	0.44	0.00	0.00
311	Physical and engineering science technicians	7.74	5.60	3.70
312	Mining, manufacturing and construction supervisors	4.82	0.00	37.10
313	Process control technicians	17.22	1.30	87.20
314	Life science technicians and related associate professionals	16.67	17.60	0.00
315	Ship and aircraft controllers and technicians	3.78	0.00	0.00
321	Medical and pharmaceutical technicians	1.88	0.00	0.00
322	Nursing and midwifery associate professionals	0.00	0.00	0.00

323	Traditional and complementary medicine associate professionals	4.08	0.00	0.00
324	Veterinary technicians and assistants	5.58	0.00	0.00
325	Other health associate professionals	5.89	0.30	0.00
331	Financial and mathematical associate professionals	0.53	0.20	0.00
332	Sales and purchasing agents and brokers	2.94	6.70	0.00
333	Business services agents	1.63	0.60	0.00
334	Administrative and specialised secretaries	0.00	0.00	0.00
335	Regulatory government associate professionals	3.93	0.00	0.00
341	Legal, social and religious associate professionals	0.21	0.00	0.00
342	Sports and fitness workers	3.99	0.00	0.00
343	Artistic, cultural and culinary associate professionals	1.42	0.00	0.00
351	Information and communications technology operations and user support technicians	0.00	0.00	0.00
352	Telecommunications and broadcasting technicians	0.65	0.00	0.00
411	General office clerks	0.00	0.00	0.00
412	Secretaries (general)	0.00	0.00	0.00
413	Keyboard operators	0.00	0.00	0.00
421	Tellers, money collectors and related clerks	0.32	0.00	0.00
422	Client information workers	4.52	0.00	0.00
431	Numerical clerks	0.00	0.00	0.00
432	Material-recording and transport clerks	4.17	1.80	0.00
441	Other clerical support workers	0.49	0.00	0.00
511	Travel attendants, conductors and guides	8.84	0.00	0.00
512	Cooks	3.54	0.00	0.00
513	Waiters and bartenders	0.97	0.00	0.00
514	Hairdressers, beauticians and related workers	0.64	0.00	0.00
515	Building and housekeeping supervisors	5.43	0.00	0.00
516	Other personal services workers	5.25	0.00	0.00
521	Street and market salespersons	0.00	0.00	0.00
522	Shop salespersons	0.62	0.00	0.00
523	Cashiers and ticket clerks	0.00	0.00	0.00
524	Other sales workers	0.34	0.00	0.00
531	Childcare workers and teachers' aides	1.02	0.00	0.00
532	Personal care workers in health services	0.77	0.00	0.00
541	Protective services workers	4.02	0.00	0.00
611	Market gardeners and crop growers	32.31	0.00	0.00
612	Animal producers	9.95	0.00	0.00
613	Mixed crop and animal producers	35.19	0.00	0.00
621	Forestry and related workers	57.89	0.00	4.50
622	Fishery workers, hunters and trappers	7.53	0.00	0.00
631	Subsistence crop farmers	32.31	0.00	0.00
632	Subsistence livestock farmers	9.95	0.00	0.00
633	Subsistence mixed crop and livestock farmers	35.19	0.00	0.00
634	Subsistence fishers, hunters, trappers and gatherers	7.53	0.00	0.00
711	Building frame and related trades workers	6.13	1.70	0.10
712	Building finishers and related trades workers	9.81	10.50	0.00
713	Painters, building structure cleaners and related trades workers	13.99	0.00	15.90
721	Sheet and structural metal workers, moulders and welders, and related workers	1.09	3.60	2.90
722	Blacksmiths, toolmakers and related trades workers	0.34	1.70	25.50
723	Machinery mechanics and repairers	2.70	1.60	7.60
731	Handicraft workers	1.97	0.00	6.10

732	Printing trades workers	0.13	0.00	0.00
741	Electrical equipment installers and repairers	8.47	0.00	8.20
742	Electronics and telecommunications installers and repairers	1.98	0.00	1.80
751	Food processing and related trades workers	4.01	0.00	31.70
752	Wood treaters, cabinet-makers and related trades workers	4.16	0.00	100.00
753	Garment and related trades workers	2.88	0.00	32.40
754	Other craft and related workers	3.66	4.90	1.10
811	Mining and mineral processing plant operators	1.99	0.60	95.20
812	Metal processing and finishing plant operators	1.22	0.00	100.00
813	Chemical and photographic products plant and machine operators	5.89	0.90	60.30
814	Rubber, plastic and paper products machine operators	2.35	0.00	73.20
815	Textile, fur and leather products machine operators	2.64	0.00	13.90
816	Food and related products machine operators	4.27	0.00	85.70
817	Wood processing and papermaking plant operators	6.67	0.00	100.00
818	Other stationary plant and machine operators	4.40	0.00	88.20
821	Assemblers	2.63	0.20	0.00
831	Locomotive engine drivers and related workers	0.00	0.00	1.40
832	Car, van and motorcycle drivers	0.00	0.00	0.00
833	Heavy truck and bus drivers	5.72	6.90	0.00
834	Mobile plant operators	5.95	0.00	3.20
835	Ships' deck crews and related workers	3.29	0.00	0.00
911	Domestic, hotel and office cleaners and helpers	6.00	0.00	0.00
912	Vehicle, window, laundry and other hand cleaning workers	6.86	0.00	0.50
921	Agricultural, forestry and fishery labourers	16.41	0.00	0.00
931	Mining and construction labourers	5.54	12.10	1.70
932	Manufacturing labourers	3.70	2.70	2.30
933	Transport and storage labourers	2.65	1.80	0.00
941	Food preparation assistants	6.45	0.00	0.00
951	Street and related service workers	0.00	0.00	0.00
952	Street vendors (excluding food)	0.00	0.00	0.00
961	Refuse workers	47.32	38.70	0.00
962	Other elementary workers	3.14	3.30	0.50

Note: The ESCO Greenness Indicator reflects the percentage of green skills in total skills from the ESCO database. Values for ISCO codes 224, 631, 632, 633 and 634 were not provided by ESCO and imputed from similar categories for the analysis. The O*NET Greenness Indicator reflects the percentage of green tasks in total tasks from the US O*NET database, matched to ISCO codes by Bluedorn et al. (2022). Greenness indicators larger than 10% are highlighted in dark blue. The IMF Pollution Intensity reflects the frequency of occupations in pollution intensive sectors, as provided by Bluedorn et al. (2022).

Source: Authors' own calculations based on LFS and ESCO; Bluedorn et al. (2022)

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