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Let’s get green: understanding green skills and jobs through online job advertisements

Emilio Colombo
Catholic University of Milano and CRISP

Alessia De Santo
University of Milano-Bicocca and CRISP

Francesco Trentini
University of Milano-Bicocca, CRISP and LABORatorio R. Revelli

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LABORatorio R. Revelli, Collegio Carlo Alberto
Piazza Vincenzo Arbarello, 8 – 10122 Torino, Italy

Tel. +39 011 670.50.60
www.laboratoriorevelli.it – labor@ laboratoriorevelli.it

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Emilio Colombo[†]
Università Cattolica
CRISP

Alessia De Santo [‡]
University of Milano-Bicocca
CRISP

Francesco Trentini [§]
University of Milano-Bicocca
CRISP
LABORatorio "R. Revelli"

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[†]Email: emilio.colombo@unicatt.it.
[‡]Email: alessia.desanto@unimib.it
[§]Email: francesco.trentini@unimib.it

Abstract

Green jobs and skills are pivotal to global and European efforts toward an environmentally sustainable economy and climate neutrality. Understanding their characteristics is vital for designing policies that address workforce challenges during this transition. Existing literature often analyzes green jobs using occupations as a proxy, either categorizing entire occupations as green or assigning greenness scores based on tasks (Bowen et al. (2018); Vona et al. (2019)). This study extends the analysis by focusing on green skills, leveraging data from Eurostat's Web Intelligence Hub on Online Job Advertisements (OJA). This dataset allows us to observe skill requirements at the job advertisement level, revealing heterogeneity within occupations. We analyze green OJAs—ads featuring at least one green skill—at the ISCO08 IV-digit level across 26 European countries (2019–2023). We find that green OJAs are linked to higher education requirements, higher wages, and lower experience demands. Additionally, introducing an occupation greenness score, we find that green OJAs in brown occupations – jobs with zero greenness - also command a wage premium. The granularity of our data allows us to provide evidence on the specificity of skill bundles for green occupations, differences in skill demand at the extensive and intensive margin, and complementarities between green skills and other skill types. More specifically green OJAs emphasize social, communication, and management skills. They also rely more on distinctive, specialized cognitive and manual skills.

Keywords: green skills, green jobs, online job advertisements

JEL codes: J21, J24, J63.

1 Introduction and Motivation

Green jobs and green skills are at the forefront of the global and European political agenda for the ongoing effort to transition to an environmentally sustainable economy. In 2019, the European Green Deal set out a comprehensive development strategy that pivoted on a structural transformation of the EU into a climate-neutral competitive economy by 2050. What distinguished the European Green Deal from previous strategies was its core focus on environmental aspects, which have quickly translated into a set of legislative actions (D'Amato et al., 2024; Paleari, 2022) and backed by substantial investments. The European Commission committed to €1 trillion in sustainable investments until 2030 through Next Generation EU and the EU seven-years budget, and the implementation was reinforced through all main EU initiatives such as the European Year of Skills in 2024.

The green transition is expected to bring significant changes to labor markets. On the one hand, it offers new opportunities for job creation in areas such as the circular economy, sustainable transport, and renewable energy production. On the other hand, it may negatively impact certain sectors, leading to job losses in highly polluting industries (Maldonado et al., 2024; Cedefop, 2022). Job mobility from polluting activities to non-polluting ones is already a driver of greening (Maczulskij, 2024), but targeted policies should be introduced to mitigate these challenges while leveraging opportunities offered by the investments in this area (Causa et al., 2024; Vandeplas et al., 2022). Comprehensive industrial and labor policies are also necessary to leverage the characteristics of local economies (Rodríguez-Pose and Bartalucci, 2023; Moreno and Ocampo-Corrales, 2022; Barbieri and Consoli, 2019) considering the interplay with other factors, especially digitalization (Cicerone et al., 2023; Santoalha et al., 2021).

To address this critical need, our analysis focuses specifically on identifying and analyzing green skills, an aspect that has been somewhat under-explored by the rest of the literature. We do so by analyzing a large and unique set of Online Job Advertisements (OJAs) across 26 European countries for the period 2019-2023. Our paper contributes to the literature in several dimensions. First, we shift the level of observation from tasks to skills. The latter provides the opportunity to examine the competencies required to perform a job, rather than the activities to be performed, as in the former. This is a significant methodological innovation that offers greater flexibility in the analysis of green jobs. In fact, the categorization of tasks in green and non-green ones leads to a definition of green occupations that is invariant across dimensions that are of high interest for the economic analysis, namely different local labor markets, economic sectors, and time. On the contrary, we are able to account for those differences at a very granular level. Second, we provide a different perspective in analyzing green jobs. According to the task approach, green jobs coincide with green occupations; our approach allows an analysis *within* occupation, distinguishing between OJAs that contain green skills from those that don't. This framework does not conflict with the tasks approach but rather complements it, enabling the study of the role of green skills outside the usual boundaries, for example in the demand of brown occupations. Third, the detail at skill level also allows us to derive evidence on the specificity of skill bundles for green occupations, differences in skill demand at the extensive and intensive margin, and complementarities between green skills and other skill types. Finally, our work presents an analysis of green jobs in the European labor market. Most of the literature focuses on the US due to data availability, but this also implies that the external validity of the results is limited, both in terms of the economic setting and in terms of the taxonomies used to classify green jobs. In such cases, occupational tasks are characterized using O*NET, built on the US market using the SOC classification system, which is difficult to be trans-coded into other classifications without misalignment errors. In our study, we use data on Europe that is classified according to the ESCO European taxonomy.

The remainder of the paper is structured as follows: section 2 illustrates the data set and the methodology, section 3 presents the empirical analysis on green OJAs and green occupations, section 4 illustrates the findings on skill bundles, and finally section 5 concludes.

2 Data and methodology

This study uses data from the Web Intelligence Hub (WIH), a platform created by Eurostat to standardize methods and tools for web data collection for the production of official statistics. The most advanced application of this platform is WIH-OJA, developed in cooperation with the European Center for the Development of Vocational Training (Cedefop). The system automatically collects online job advertisements (OJA) from approximately 1,000 sources across Europe, including the main public and private actors in the online labor market, such as specialized job boards, public employment services, private employment agencies' websites, and the job sections of national newspapers. OJAs are downloaded and analyzed to extract key information, including job title, job description, geographic location, economic sector of the hiring organization, and skill requirements (Cedefop, 2019). The extracted structured and unstructured information is used to classify the data according to the official taxonomy of the European Union, the European System of Skills, Competences, Qualifications and Occupations (ESCO), reaching the 4th level of the International Standard of Occupational Classification (ISCO). In addition, a variety of other aspects of OJAs are extracted and classified according to the main international standards: location (NUTS), educational (ISCED Levels)[1], economic activity (NACE Rev.2 Divisions) and skills (ESCO skill concepts). More specifically, skill classification is based on a framework of techniques that uses the ESCO Skills pillar taxonomy, which includes almost 14000 skills, as a reference dictionary of skill names and synonyms as inputs for a classifier.[2] Considering the large number of skills that emerge from the data, we also introduce an aggregate coarse classification that distinguishes between Cognitive, Digital, Manual, Management, and Social and Communication skills (see details in Table 8).

Information on the level of experience is available on an 8-point scale according to Table 11, while wages are available on a 13-point scale corresponding to the wage bands described in Table 10.

To perform the analysis, we kept all OJAs for which we have information on occupation, wages, education, experience, and skills for the period 2019-2023. This leaves us with around 30 million observations, spread across 353 ISCO-08 IV digit occupations, 21 sectors, and 26 European countries.

The use of wage information considerably restricts the sample, as most OJAs do not report the offered wage. This is not a limitation for our analysis for three reasons. First, the sample restriction still leaves us almost 30 million observations, 10% of the complete dataset, enough to conduct a detailed analysis; second, because we perform an analysis within occupation, we are less concerned about possible sample selection bias. Third, the results of the analysis conducted for the other variables (education and experience) on a larger dataset are in line with those obtained on the subset that reports the wage information.[3]

2.1 Green jobs vs Green OJA

A considerable body of research has emerged to explore the concept of green jobs; however, a universally accepted definition remains elusive. There are two primary approaches to empirically identifying green jobs (Apostel and Barslund, 2024). The first approach classifies industries or companies as green, considering all workers within these entities as holding green occupations, and is therefore referred to as the entity-level approach. To identify green industries and companies, researchers often employ either top-down or bottom-up methodologies. Top-down approaches involve classifying entire sectors as green, whereas bottom-up methods focus on identifying specific companies or establishments as green. However, top-down strate-

[1] See table 9 for the detailed classification

[2] In this work we exclude skills that belong to the ESCO *languages and knowledge* concept groups, to focus on ESCO concepts that represent skills as know-how: professional, transversal, and digital skills.

[3] Results available upon request.

gies may overlook green jobs present in non-green sectors, and certain bottom-up methods are similarly prone to disregarding specific green activities.

The second approach moves from a different starting point, which is the analysis and categorization of individual occupations as green or non-green, and is known as the occupation-specific approach. This approach can be further developed by analyzing tasks within occupations, shifting from a binary classification of "green" or "non-green" jobs to a continuous measure that quantifies the extent of greenness in occupational activities. Under this framework, green jobs are not confined to specific sectors but can be present across a wide range of industries, with their degree of "greenness" determined by the proportion of time dedicated to green tasks (Bowen et al. (2018); Vona et al. (2019)). The studies using task-based green measures have generally aimed to identify the characteristics of green jobs as opposed to non-green ones (Peters (2014); Consoli et al. (2016); Curtis and Marinescu (2022); Curtis et al. (2024)). Another subset of the literature examines the relationship between environmental policy and green employment, but this research mainly focuses on regional levels and explores how green initiatives can foster green skills and create green jobs (Vona et al. (2018, 2019)).

Our approach differs considerably from the studies described above. Instead of identifying green occupations according to a description of tasks and activities such as the ones by O*NET (see Vona et al. (2019)), we look *into* occupations differentiating jobs according to their skill content. We use Online Job Advertisements (OJA) data and build an analysis of green jobs, identified through green skills requirements and explore their characteristics and skill content. This is because we can distinguish, *within* occupations, green OJAs from other OJAs. In this regard, we complement the task-based approach by looking at the competencies required to workers to complete such tasks, i.e., skills requested by employers in job postings for such positions.[4]

Moreover, by focusing on the skill content of jobs, we address one of the main criticisms of the task-based method, which is that within similar occupations, there may be substantial differences in task content that are not captured by occupational-level data (Apostel and Barslund, 2024). By using the skill content of the OJA, we are able to address this issue and observe within-occupation differences in skill requirements.

Since to identify green OJAs we analyze their skill requirements, the definition of green skills plays a crucial role. Green skills are identified by Eurostat using a specific classification pipeline which is determined by two conditions. First, a skill is green if it belongs to the ESCO

[4] In the literature, Autor's definition of a task is quite prominent: a task is "a unit of work activity that produces output"(Autor, 2013). In contrast, a skill refers to the capability of executing tasks. Skills are determined by various factors such as education, training, and experience (Apostel and Barslund, 2024).

Green Skills group.[5] Second, green skills have been augmented by means of green terms identified by Cedefop (Cedefop, 2024). The result is a data-driven taxonomy that enriches the standard ESCO classification.[6]

While the major part of our analysis is conducted within occupations, to deepen the analysis we will also employ a classification of green occupations. For this purpose, we will use the OECD Greeness measure (Scholl et al., 2023).[7]

To summarize, we will use two distinct concepts to categorize green job ads:

- **Green OJA**. Refers to an OJA that includes at least one Green skill. Each OJA is assigned an occupation code at the ISCO-08 IV digit level. The distinction between green and non-green OJAs is therefore done *within* occupation.

- **Green/Brown Occupation**. An occupation classified as "Green" if it is characterized by a positive value of OECD Greenness score as opposed to "Brown" occupations. The value is assigned at the ISCO-08 IV digit level occupation code and is therefore invariant for OJA belonging to the same occupation code.

2.2 Descriptive statistics

The final dataset comprises 26 Countries,[8] 353 Esco Occupations and 29,236,393 unique OJAs, of which 1,419,207 (5%) are classified as green.

The following graphs provide an overview of the dataset, illustrating the distribution of all OJAs and the subset of green OJA over the dependent and control variables. As shown in Fig.1, the distributions for green and non-green OJAs highlight some general features of green jobs. Green OJAs are more concentrated in professional, scientific, and technical activities (M), manufacturing (C), energy supply (D), water supply and sewage management (E), construction (F) and financial and insurance activities (K). Green OJA are also more concentrated in high education levels and high wages, while no differences emerge concerning experience.[9] Regarding occupation groups, OJA are more concentrated in high-skill occupations (managers, professionals, and technicians, ISCO-08 Major group 1, 2, and 3, respectively) and specialized workers (craft and related trades workers and plant and machine operators, ISCO-08 Major

[5] https://esco.ec.europa.eu/en/about-esco/publications/publication/green-skills-and-knowledge-concepts-labelling-esco

[6] The detailed description of the construction of the green skill taxonomy is provided in Appendix B.

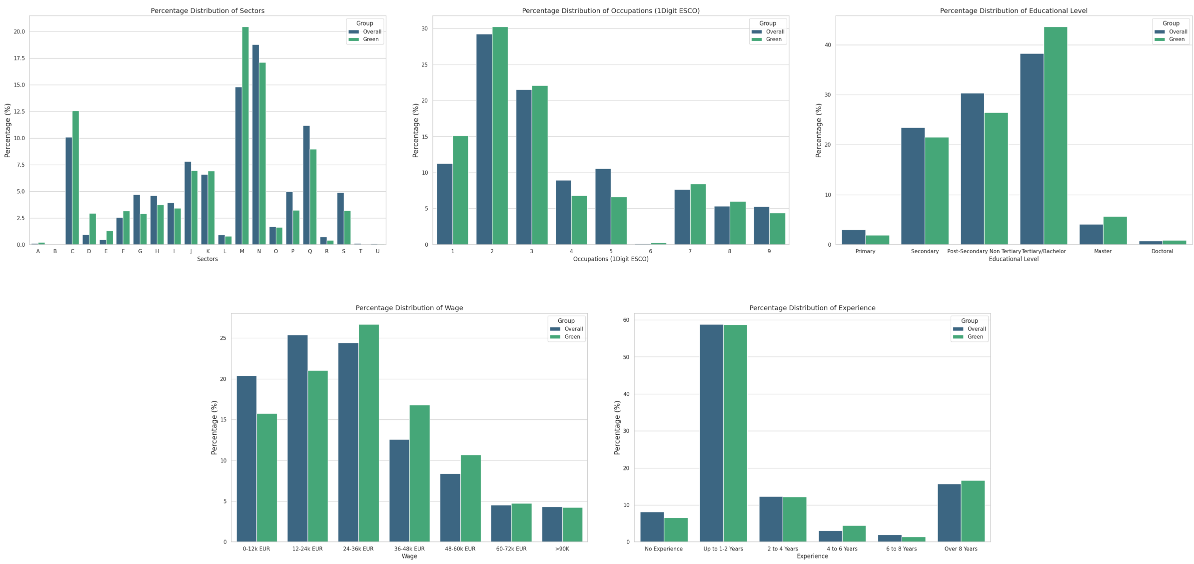
[7] See 3.4 for a detailed discussion of this Index.

[8] We retain the UK and all European Countries, except for Estonia and Lithuania due to the low number of observations.

[9] For sake of readability, we have introduced a coarse group classification for wage, experience, and education with respect to that used in the regression analysis, which are presented in tables 11, 10, and 9.

group 7 and 8, respectively), while they have lower shares of support personnel, retail sales workers, and elementary occupations (clerical support workers, service and sales workers, and elementary occupations' workers, respectively ISCO-08 Major groups 4, 5, and 9).[10]

Figure 1: Percentage distribution of Green and not-Green OJA for all dataset variables



Note: authors' calculations on WIH-OJA data

3 Findings

3.1 Profiling of Green OJA

We start by presenting the main overall result for European countries. We explore green OJA profiles by relying on a model specification borrowed from Consoli et al. (2016) and summarised by the following equation:

$$y_{i,c,s,t} = \alpha + \beta Green_{i,c,s,t} + \Gamma FE_{i,c,s,t} + \epsilon_{i,c,s,t} \tag{1}$$

where $y_{i,c,s,t}$ is a measure of outcome for occupation i, country c sector s in year t. The outcome is the level of education, experience, wage, $green$ is dummy variable indicating if the OJA contains at least one green skill (1) or not (0). The model is saturated with very detailed fixed effects for country, occupation (ISCO-08 IV digit) economic activity (NACE

[10] Compared to actual employment distributions in Europe, OJA distribution is more skewed towards high-skill occupations. This overrepresentation reflects the higher propensity for high-skill positions to be advertised online relative to low-skill positions. However, this sampling characteristic does not bias our analysis, as there is no theoretical or empirical basis to suggest that green job advertisements follow different online posting patterns than non-green positions.

divisions) and time (2019-2023). The key variable of interest, *green*, indicates whether an OJA is classified as green, meaning that it contains at least one green skill. Table 1 shows that the coefficients for *green* are significant across all models, with positive sign for education and wage, and a negative for experience. Given the number of controlling fixed effects, the interpretation of our result is that within occupations, sector, country and year, OJAs that contain green skills have higher education and wage and less required experience. Thus, green skills carry a wage and occupation premium and an experience discount.

Table 1: Profiling of green occupations: education, experience and wage

	Education	Experience	Wage
Green OJA	0.0466***	-0.0158***	0.171***
	(0.000987)	(0.00191)	(0.00254)
Constant	4.282***	3.401***	5.381***
	(0.000212)	(0.000408)	(0.000555)
Isco FE	✓	✓	✓
Time FE	✓	✓	✓
Sector FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	29236392	29236392	29236392
R^2	0.281	0.068	0.152

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an OJA. OLS regression using education, wage and experience as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Since the seminal paper by Mincer (1958) there is a well-documented correlation between wage experience and education. Therefore, we augment the wage regression following a Mincer-style earning function by adding education and experience as controls. We also augment the experience regression by controlling for the level of education. Table 2 shows that the sign and magnitude of the $green$ dummy barely change, even adding as controls interaction terms between occupation and economic activity sector.

3.2 Profiling of green OJAs over time

Albeit our data does not provide long time series, it is worth to analyze whether the evidence collected above is stable over time. This is done by interacting the green dummy with a time index. Figure 2 plots the estimated coefficients. Overall, the general message is that the education and wage premium carried by green skills hold irrespective of the time period. Note that the wage premium is considerably reduced in 2020 and 2021. This can be explained by

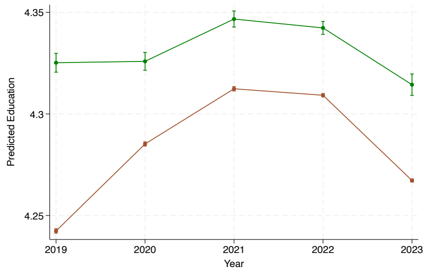
Table 2: Regression Results with additional regressors

	Education	Experience	Wage
Green OJA	0.0466***	-0.0166***	0.169***
	(0.000987)	(0.00191)	(0.00253)
Education		0.0174***	0.0701***
		(0.000356)	(0.000499)
Experience			0.0857***
			(0.000257)
Constant	4.282***	3.326***	4.789***
	(0.000212)	(0.00158)	(0.00236)
Sector FE	✓	✓	✓
Isco FE	✓	✓	✓
Isco*Sector FE	✓	✓	✓
Time FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	29236392	29236392	29236392
R^2	0.281	0.068	0.152

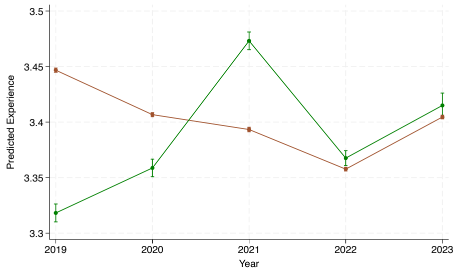
Source: Authors' calculation on WIH-OJA data.
Notes: Each observation consists of an OJA. OLS regression using education, wage and experience as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

the fact that during the Covid period the slowdown in labor demand heavily compressed wage differentials. This pattern is consistent with the sharp increase in experience requirements during the same period. The labor market slack induced by the Covid-19 enabled employers to impose higher experience requirements without corresponding wage premiums, reflecting their enhanced bargaining power relative to job seekers. Note also that as the green premium is clearly present already in 2019, it is likely to be driven by structural elements rather than by policy factors such as the Next Generation EU 2020's plan, which poses a significant emphasis on the green transition. With respect to experience, the negative premium displayed in tables 1 and 2 appears to be mainly driven by the first years of the sample. Yet, the time series reveals that in general experience requirements have been having opposite developments through time: non-green OJA have witnessed a reduction in requirements, while green OJA's requirements have been growing across the period, with an alignment in 2022 and 2023. This evidence suggests that green technologies have reached a level of maturity and, therefore, standardisation, which makes them similar to other firms' technologies, making the recruitment policies for green and non-green workers to align.

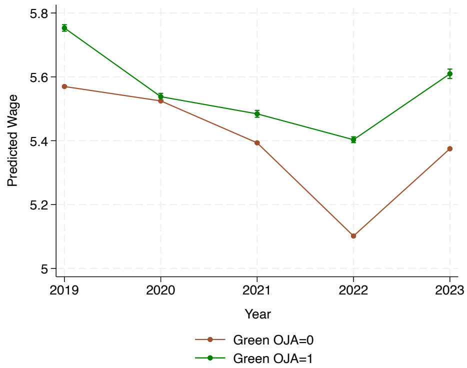
Figure 2: Interaction effects: Time variable with Green OJA Dummy



(a) Years and Education



(b) Years and Experience



(c) Years and Wage

Note: authors' calculations on WIH-OJA data

3.3 Profiling OJAs with green skills intensity

As emphasized in the previous paragraphs, our green measure divides OJAs into green and non-green ones, dichotomizing the degree of greenness of an OJA with a binary indicator. However, some OJAs contain more than one green skill. It is interesting then to analyze whether our results also capture the intensive margin of the degree of greenness. In table 3 we replaced the green dummy with two different indicators. The first is the percentage of green skills in an OJA out of the total number of skills mentioned, following the intuition that the relative concentration of green skills within a job posting better captures the extent to which green competencies are core to the skill profile required for the job, rather than marginal. The second is a simple count of green skills, which shifts the focus to the absolute quantity of green competencies required, regardless of their proportion to other required skills. Table 3 shows that, also considering the intensive margin, most of the intuition is confirmed: higher greenness carries a higher education and wage premium, while experience remains negative when considering the count and becomes positive but not significant when considering the percentage of green skills.

Table 3: Baseline Regression for Green Skills Fraction (%) and Count

	Education	Experience	Wage	Education	Experience	Wage
Green Skills (%)	0.00201***	0.000124	0.00538***	–	–	–
	(0.0000633)	(0.000117)	(0.000163)			
Green Skills Count	–	–	–	0.0200***	-0.0165***	0.0442***
				(0.000456)	(0.000836)	(0.00105)
Education	–	0.0130***	0.0680***	–	0.0130***	0.0679***
		(0.000361)	(0.000505)		(0.000361)	(0.000505)
Experience	–	–	0.0828***	–	–	0.0829***
			(0.000257)			(0.000257)
Constant	4.283***	3.344***	4.813***	4.283***	3.345***	4.813***
	(0.000206)	(0.00160)	(0.00238)	(0.000206)	(0.00160)	(0.00238)
ISCO FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Isco*Sector FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Observations	29236273	29236273	29236273	29236273	29236273	29236273
R^2	0.304	0.078	0.169	0.304	0.078	0.169

Source: Authors' calculation on WIH-OJA data.

Note: Each observation consists of an OJA or Green OJA. OLS regression using education, experience, and wage as the dependent variables. Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

3.4 Green skills and green occupations

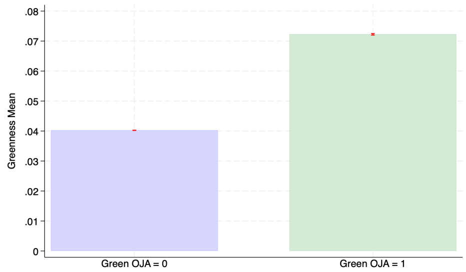
So far we have identified green OJAs by focusing on their skill content, regardless of the type of occupation to which the OJA relates. As stressed in section 2.1 our approach in this regard differs significantly from most of the literature, which has focused on *occupations* that have been classified as green according to the specific tasks that compose them. As a next step, we integrate both approaches by analyzing the relationship between green OJAs and green occupations. For this purpose, we adopt the OECD measure of green occupations as described by Scholl et al. (2023). This index builds on the greenness metrics originally developed by Consoli et al. (2016) and Vona et al. (2018) who, relying on the detail of the O*NET database for the United States, define an occupation Greenness as the share of green-specific tasks in the total specific tasks within each occupation. The OECD measure is computed by adapting these measures from the Standard Occupational Classification (SOC) system used in the US, to the International Standard Classification of Occupations (ISCO-08) at a detailed 4-digit level.

Green OJAs and green occupations are clearly related: the mean greenness is significantly higher for OJA containing green skills as documented by figure 3.[11]

The introduction of green occupations allows us to investigate more thoroughly the proper-

[11] Appendix D provides some descriptive statistics of the distribution of green occupations in our sample.

Figure 3: Mean greenness by OJA group



Note: authors' calculations on WIH-OJA data

ties of green OJAs, in particular whether these features are limited to green occupations or are transversal to other occupations.

We start the analysis with a binary distinction between green and brown occupations. The former are those with a positive degree of greenness assigned by the OECD, while the latter are the remaining ones. To explore the transversal nature of green skills, we start by focusing on brown occupations. In table 4 we add a brown occupation dummy and its interaction with the OJA green dummy.

Brown occupations are characterized by a lower degree of education, experience, and wage, confirming the results obtained by Consoli et al. (2016) for the US. Interestingly, the interaction term shows that the premium for having green skills is actually stronger for brown occupations. Thus, the presence of green skills required by the OJA carries a premium that is particularly strong for occupations that are not explicitly characterized as green. This evidence is particularly important because it shows the general importance of green skills, which are widespread across occupations and are priced by the market even in non-green occupations.

Next, we focus on the restricted sample of green occupations (Tables 5 and 6).[12] The overall effect for the green OJA indicator is confirmed. Interestingly the greeness effect alone is not entirely in line with the findings of Consoli et al. (2016). Apart from the obvious difference between the EU and US market, the reason is likely due to the fact that their result is a combination of the extensive (being green or not) and intensive margin (degree of greenness) of occupations. In our case, while in table 4 we have looked at the extensive margin, here we focus on the intensive one. Considering only OJA without green skills, those in occupations characterized by a higher degree of Greenness are associated with higher education but with lower experience and wages. The interaction term shows, however, a premium for education and experience on the presence of green skills in the OJA. The wage premium is on the other

[12]The sample is consistently reduced as we limit the observations to only green occupations

Table 4: Regression results with OECD Brown occ. dummy

	Education	Experience	Wage
Green OJA	0.0359***	-0.0478***	0.148***
	(0.00165)	(0.00326)	(0.00418)
Brown occupation	-0.0844***	-0.0539***	-0.0351***
	(0.000895)	(0.00180)	(0.00237)
Green OJA × Brown occupation	0.00420*	0.0554***	0.0383***
	(0.00205)	(0.00400)	(0.00522)
education		0.0178***	0.0709***
		(0.000357)	(0.000498)
experience			0.0872***
			(0.000257)
Constant	4.346***	3.365***	4.807***
	(0.000701)	(0.00209)	(0.00297)
Isco FE (Digit 3)	✓	✓	✓
Sector FE	✓	✓	✓
Isco*Sector FE	✓	✓	✓
Time FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	29233060	29233060	29233060
R^2	0.279	0.070	0.158

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an OJA. We define Brown occupations as the ones not classified as green in the OECD classification. OLS regression using education, experience, and wage as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5: Regression Results with OECD Greenness Levels (Only Greenness > 0)

	Education	Experience	Wage
Green OJA	0.0381***	-0.0811***	0.199***
	(0.00236)	(0.00456)	(0.00592)
Greenness	0.227***	-0.146***	-0.111***
	(0.00598)	(0.0108)	(0.0145)
Green OJA × Greenness	-0.0130	0.113***	-0.257***
	(0.00942)	(0.0174)	(0.0220)
education		0.0556***	0.0564***
		(0.000776)	(0.00102)
experience			0.110***
			(0.000491)
Constant	4.432***	3.375***	5.082***
	(0.00105)	(0.00395)	(0.00546)
Isco FE (Digit 3)	✓	✓	✓
Sector FE	✓	✓	✓
Isco*Sector FE	✓	✓	✓
Time FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	7433134	7433134	7433134
R^2	0.246	0.048	0.145

Source: Authors' calculation on WIH-OJA data.

Note: Each observation consists of an OJA of a Green Occupation according to the OECD Classification. OLS regression using education, experience, and wage as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

hand negative. To further explore these effects, we split the greenness index into quartiles, analyzing the marginal effects at different levels of greenness and its interaction with the presence of green skills in the OJA.

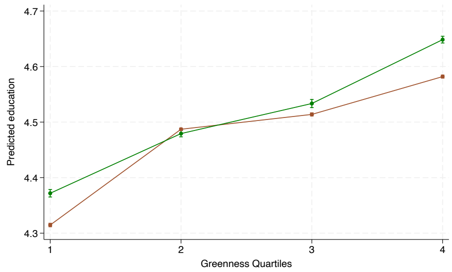
Results are shown in Tab. 6. For non-green jobs, that is for OJAs that do not mention green skills, the greenness effect is positive and generally increasing in the degree of greenness. Notably, the effect is monotonic in education requirements and wage offers. Considering the interaction effect, the premium associated with green skills within green occupations, we observe a growing relation for education requirements, and this is true in particular for occupations in the highest greenness quartile. For the intermediate quartiles (Q2 and Q3) the effects are more nuanced; however, the general finding is that higher greenness carries a higher premium in all three variables, as shown in Fig. 4. An explanation for this evidence is that green know-how is perceived as a standard feature within green occupations, and this association is stronger the higher the level of greenness of the occupation. In highly green occupations, which probably present a more standardized task bundle, the wage gap between green and brown OJA is smaller, indicating a smaller premium. Furthermore, the composition of occupations within these quartiles may contribute to the observed effects. Specifically, Q1 and Q4 have a more distinct occupational composition—highly skilled occupations dominate Q4, while elementary occupations are more prevalent in Q1. In contrast, Q2 and Q3 exhibit a more diverse mix, encompassing occupations across the whole ISCO-08 taxonomy (see Fig. 9).

Table 6: Regression results with categorized greenness

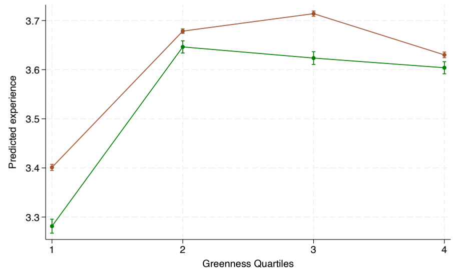
	Education	Experience	Wage
Green OJA	0.0572***	-0.120***	0.177***
	(0.00322)	(0.00690)	(0.00950)
Greenness Q2	0.172***	0.277***	0.107***
	(0.00210)	(0.00436)	(0.00571)
Greenness Q3	0.199***	0.313***	0.167***
	(0.00249)	(0.00471)	(0.00642)
Greenness Q4	0.267***	0.229***	0.203***
	(0.00260)	(0.00528)	(0.00701)
Green OJA × Greenness Q2	-0.0650***	0.0876***	0.0248*
	(0.00436)	(0.00934)	(0.0124)
Green OJA × Greenness Q3	-0.0376***	0.0294**	-0.00239
	(0.00492)	(0.00952)	(0.0127)
Green OJA × Greenness Q4	0.00939*	0.0936***	-0.126***
	(0.00443)	(0.00924)	(0.0122)
education		0.0540***	0.0552***
		(0.000777)	(0.00102)
experience			0.110***
			(0.000491)
Constant	4.315***	3.160***	4.956***
	(0.00160)	(0.00462)	(0.00631)
Isco FE (Digit 3)	✓	✓	✓
Sector FE	✓	✓	✓
Isco*Sector FE	✓	✓	✓
Time FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	7433134	7433134	7433134
R^2	0.247	0.048	0.145

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an OJA of a Green Occupation according to the OECD Classification. OLS regression using education, experience, and wage as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

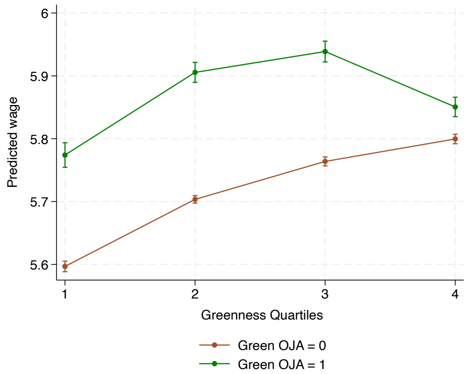
Figure 4: Interaction Effects: Green OJA and Greenness Quartiles on Human Capital variables



(a) Greenness Quartiles and Education



(b) Greenness Quartiles and Experience



(c) Greenness Quartiles and Wage

4 Analysing green-jobs skill bundles

After defining the characteristics of green OJAs and examining their relationship with green occupations, we now focus on analyzing the skills associated with green OJAs. Beyond specific green skills, we aim to explore whether green and non-green OJAs differ in their skill requirements.

Within the task-based approach, several studies have addressed this question by utilizing O*NET green jobs classifications and the detailed information on occupations and their task content available in the O*NET database (Valero et al. (2021)). These studies have found that green jobs are characterized by a greater emphasis on non-routine analytical tasks (Bowen et al. (2018); Consoli et al. (2016)). Additionally, Vona et al. (2018), highlights two key sets of green skills that distinguish green jobs from non-green jobs: engineering skills for designing and producing green technologies, and managerial skills for implementing and overseeing environmental organizational practices. We sought to explore these differences in line with this body of work. However, as explained in section 3.4 our approach diverges from the existing literature by focusing on the skills demanded in green jobs, rather than on the activities (tasks) performed in green occupations as defined by O*NET.

The assessment is developed along two main dimensions, that highlight different aspects of the characteristics of skill requirements. First, in section 4.1, we study the differences in the *variety of skill bundles* between green and non-green jobs within occupations, underscoring the skill types that overlap or are unique between them. Second, in section 4.2, we address the topic of the s*pecialization of skill requirements* of green jobs in comparison with non-green ones, to infer which skill groups are characteristic for them.

4.1 Variety of the skill bundles

In order to meaningfully compare skill requirements, we excluded green skills from the skill sets of green OJAs and focused on the differences in the remaining skill bundles.

First we construct a simple measure of dissimilarity between skill-sets. This is done by computing the Jaccard distance, defined as follows:

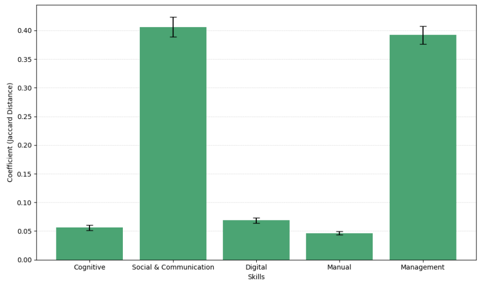
$$J_i = 1 - \frac{S_{(i,g)} \cap S_{(i,ng)}}{S_{(i,g)} \cup S_{(i,ng)}} \tag{2}$$

where i represents the occupation, g represents the green OJA (Online Job Advertisement), and ng represents the non-green OJA (Online Job Advertisement). $S_{(i,g)}$ denotes the set of elements associated with the green OJA for occupation i, and $S_{(i,ng)}$ denotes the set of elements associated with the non-green OJA for occupation i. This formula computes the dissimilarity between the two sets $S_{(i,g)}$ and $S_{(i,ng)}$, where the numerator represents the intersection of the two sets and the denominator represents their union so that the ratio tends to 1 the more the two sets are similar. The Jaccard distance ranges from 0 to 1, with 0 indicating the sets are identical, and 1 indicating the sets have no common elements.

In appendix C, we examine the overall distribution of Jaccard distances across years, countries, and occupational groups. The trend appears generally stable over time, except for 2022, which shows a decline in the median Jaccard distance. Significant differences are also observed between countries, partly influenced by the varying number of observations included in the analysis. When analyzing occupation groups, high-skill occupations (groups 1-3) tend to display smaller median Jaccard distances, suggesting greater similarity within these groups.

Following equation (2) we computed the Jaccard distance in the skill bundle at occupation level between green and non-green OJAs; in other words, for each occupation, we constructed the skill set of green OJAs and of non-green OJAs and compared them. The Jaccard distance is the sum of the distances for all different skill types. For better interpretation, we have grouped the skills in 5 different mutually exclusive and exhaustive classes: Cognitive skills, Social

Figure 5: Composition of Jaccard Distance



Note: authors' calculations on WIH-OJA data

and communication skills, Digital skills, Manual skills, Management skills, using the ESCO taxonomy as described in table 8. In figure 5, we decompose the overall Jaccard distance in the contribution of the different groups of each group. The results show that management and social and communication skills make up most of the difference in skill bundles between green and non-green jobs.

4.2 Areas of skill specialization of green jobs

The Jaccard distance allows to identify the elements that quantitatively contribute to the differences between the skill sets of green and non-green occupations. However, the Jaccard distance is a "neutral" measure as it does not provide insight into the specialization of green occupations—specifically, which skills are specific and most significant for these jobs. To address this research question, we use a measure rooted in the revealed comparative advantages (RCA) concept. This class of indicators was first developed in international trade theory by Balassa (1965). The rationale is to use post-trade measures to infer the comparative advantages in the production of traded goods of a region in a multilateral context. More recently, RCA has been translated into the economic geography literature to describe regions' specialization in productive activities (see van Dam et al. (2023) for an overview of the literature and the most recent advances). In the labor market, a notable application of this concept is provided by Alabdulkareem et al. (2018) who apply it to the skill distribution using the O*NET intensity measures. In analogy with this solution, we adopt skill frequency as a measure of relevance of skill demand for each occupation and derive our measure of skill specialization based on the concept of revealed comparative advantages.

For each year of observation t, we define a set of ISCO-08 IV digit occupation $O_t = o_k, k = 1, \ldots, K_t$ and its skill set $S_t = s_j, j = 1, \ldots, J_t$ defined on the domain of observed skill in the European online labor market. We define the skill frequency as:

$$sf_{ij} = \frac{\sum_{k=1}^{n} I(o_k = o_i) \cdot I(s_i = s_j)}{\sum_{k=1}^{n} I(o_i = o_k)} \tag{3}$$

where I denotes the indicator function and $\sum_{k=1}^{n} I(o_k = o_i) \cdot I(s_k = s_j)$ the count of the occurrences of the skill s_j for occupation o_k. The term $\sum_{i=1}^{n} I(o_i = o_k)$ represents the total number of observations of occupation o_k. Iterating over skills and occupations, we obtain a matrix $\underset{O_t \times S_t}{M}$ of the skill frequency for each pair of occupations $i \in O$ and skills $j \in S$. The revealed comparative advantage, for occupation o_i and skill s_j is defined as :

$$rca_{ij} = \frac{sf_{ij} / \sum_{j=1}^{J_t} sf_{ij}}{\sum_{i=1}^{I} sf_{ij} / \sum_{i=1}^{I} \sum_{j=1}^{J_t} sf_{ij}} \tag{4}$$

If $rca_{is} > 1$, the skill is over-represented in the occupation compared to the market, indicating a specialization in that specific skill. In the original formulation, the rca_{is} is bounded between $[0, +\infty)$ and lacks symmetry around its neutral value. To address this limitation, we use the symmetric formulation proposed by Laursen (2015), known as the Symmetric Revealed Comparative Advantage (RSCA):

$$rsca_{ij} = \frac{rca_{ij} - 1}{rca_{ij} + 1}$$

This symmetric formulation maps the metric to a homogeneous interval, with values ranging between $[-1, +1]$, improving the efficiency of the estimates in a regression framework Laursen (2015). Table 7 presents the regression results. We have computed the RSCA for each skill and grouped them following the skill taxonomy developed in the previous section. In this way, it is possible to assess the specialization of OJAs in each skill type.

Our results indicate that green OJAs possess more job-specific skills, and more rare or unique skill sets compared to their non-green counterparts. Specifically, cognitive and manual skills largely drive specialization in green OJAs. In contrast, digital and managerial skills are more commonly shared across green and non-green OJAs.

The distinction between cognitive and manual skills underlines the unique demands of green jobs, where workers frequently perform tasks that require both specialized problem-solving capabilities and practical, hands-on expertise. The homogeneous presence of digital and managerial skills across both green and non-green occupations may reflect a general trend toward digitization and the growing importance of management skills in various sectors, not just in green occupations. This finding is consistent with part of the existing literature, such as

Table 7: RSCA Results with green and not-green occupations

	RSCA
Green OJA	0.0805***
	(0.00142)
Management skills	-0.0426***
	(0.00133)
Cognitive skills	0.0840***
	(0.00194)
Digital skills	0.0930***
	(0.00186)
Manual skills	0.143***
	(0.00208)
Green OJA × Management skills	-0.00276
	(0.00210)
Green OJA × Cognitive skills	0.0232***
	(0.00313)
Green OJA × Digital skills	-0.0351***
	(0.00293)
Green OJA × Manual skills	0.00753*
	(0.00345)
Constant	0.251***
	(0.000878)
Isco FE 3Digit	✓
Time FE	✓
Country FE	✓
Observations	926671
R^2	0.056

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an occupation-skill pair. OLS regression uses the RSCA measure as the dependent variable. Robust standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

the work by Consoli et al. (2016) and Bowen et al. (2018), who find that green occupations tend to exhibit significant differences from non-green occupations, especially in terms of higher levels of non-routine, analytical skills, including creative problem-solving. The emphasis on manual skills in green OJA could further signal the non-standard nature of processes to be implemented for the transition to more sustainable production methods (Capasso et al., 2019). By integrating the findings on skill variety and specialization, we observe that cognitive and manual skills contribute only marginally to the overall difference in skill bundles between green and non-green jobs in terms of variety. However, these skills are critical in defining green jobs, as their demand is more concentrated, so that green jobs feature cognitive and manual skills that are distinctly unique compared to non-green ones.

5 Conclusions and policy implications

In the literature, the analysis of tasks substantiates some important elements regarding which parts of the job activities are relevant in green processes and provides a measure of their relevance for the occupation. The evidence emerging from our study provides complementary knowledge on the profile of green jobs from the point of view of the required skills expressed by employers. Our analysis suggests that the labor market is segmented so that green jobs are significantly different from non-green ones, even within the same narrow occupation groups. In terms of education, they have higher requirements, while firms prefer to hire less experienced workers, likely due to the specificity of the green processes in which they are involved. Most notably, the wage premium associated with the possession of green skills is significant and highlights the price that the market attaches to green competencies.

Interestingly, jobs in occupations that do not exhibit tasks related to green processes i.e. brown occupations, tend to converge to green occupations in terms of education requirement and offered wage if they require green skills, showing that the value of green skills is independent of the occupation they are listed for. Secondly, the relevance of green skills for occupations without green tasks highlights the advantages of a combined approach in grasping signals of ongoing changes in jobs as they emerge from the market. Another important aspect of green jobs is the specificity of their skill requirements. The differences in skill bundles are largely due to social, communication, and managerial skills, a larger portfolio of skills that facilitate the integration of the worker in the organization and confidently steer processes. Most importantly, what makes the profiles of green jobs unique are two other sets of skills, namely cognitive and manual ones. This suggests that workers in green jobs must pursue their activities at both the level of analytical thinking and planning, while also being proficient in hands-on, manual operations. Both terms relate to the idiosyncratic nature of the solutions that every organization can find to achieve green objectives.

These results hold significant implications for interventions and active labor market policies aimed at fostering the creation of green jobs. Based on our analysis, upskilling initiatives are expected to be more effective and less complex to implement than reskilling ones, largely due to the diverse range of competencies required for green jobs, which also aligns with the demand for higher levels of education in green jobs. Returns to effective interventions are expected to be higher than general training, considering the wage premium the market offers for green skills. Our findings also emphasize the need to integrate green principles in education and training paths for all students and learners. Finally, they suggest that an accomplished green approach to economic activities does not consist of introducing environmental sustainability as a goal but radically revisiting production processes.

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A Mappings

Table 8: Skill Groups and their Corresponding ESCO Skills Codes and Descriptions

Groups	ESCO Skill Codes	Description
Cognitive skills	S2: Information skills, T2: Thinking skills, T1.1: Mastering languages, T1.2: Working with numbers, T6: Life skills and competences	Skills related to problem-solving, information processing, and learning, including language mastery and numerical abilities.
Social and communication skills	T4: Social and communication skills, S3: Assisting and caring, S1: Communication collaboration and creativity	Skills referred to the ability to communicate, interact and engage with colleagues, clients, and customers.
Digital skills	S5: Working with computers, T1.3: Working with digital devices and applications	Skills that encompass a range of different abilities that allow an individual to use ICT tools at different levels.
Manual skills	T5: Physical and manual skills and competences, S6: Handling and moving, S7: Constructing, S8: Working with machinery and specialized equipment	Skills related to physical and manual labor, including handling, moving, constructing, and working with machinery.
Management skills	S4: Management skills, T3: Self-management skills and competences	Skills including leadership, organization, and decision-making.

Table 9: Education classes

ID	Education Level
1	Primary education
2	Lower secondary education
3	Upper secondary education
4	Post-secondary non-tertiary education
5	Short-cycle tertiary education
6	Bachelor or equivalent
7	Master or equivalent
8	Doctoral or equivalent

Table 10: Wage classes

ID	Wage Range
1	0 - 6,000 EUR
2	6,001 - 12,000 EUR
3	12,001 - 18,000 EUR
4	18,001 - 24,000 EUR
5	24,001 - 30,000 EUR
6	30,001 - 36,000 EUR
7	36,001 - 42,000 EUR
8	42,001 - 48,000 EUR
9	48,001 - 54,000 EUR
10	54,001 - 66,000 EUR
11	66,001 - 78,000 EUR
12	78,001 - 90,000 EUR
13	$>$ 90,001 EUR

Table 11: Experience classes

ID	Experience
1	No experience
2	Up to 1 year
3	From 1 to 2 years
4	From 2 to 4 years
5	From 4 to 6 years
6	From 6 to 8 years
7	From 8 to 10 years
8	Over 10 years

Table 12: Sector Category Mappings

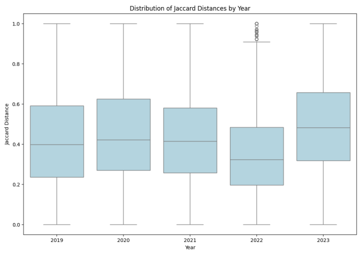
Sector Category	Code
Professional, scientific and technical activities	A
Manufacturing	B
Financial and insurance activities	C
Public administration and defence; compulsory social security	D
Administrative and support service activities	E
Human health and social work activities	F
Wholesale and retail trade; repair of motor vehicles and motorcycles	G
Accommodation and food service activities	H
Transportation and storage	I
Information and communication	J
Electricity, gas, steam and air conditioning supply	K
Other service activities	L
Construction	M
Arts, entertainment and recreation	N
Education	O
Water supply, sewerage, waste management and remediation activities	P
Real estate activities	Q
Agriculture, forestry and fishing	R
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	S
Mining and quarrying	T
Activities of extraterritorial organisations and bodies	U

B Green skill taxonomy

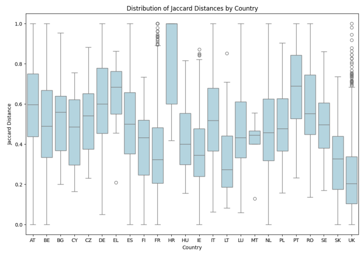
The Cedefop green skill taxonomy is a data driven taxonomy that integrates and enhances several different approaches. In a first step Cedefop has constructed a bag of green-related words (green technologies, tasks, and skills), drawing from the most relevant publications and taxonomies available. These include: a) UN System of Environmental Economic Accounting (Classification of environmental protection activities – CEPA and Classification of resource management activities -CReMA); b) International Renewable ENergy Agency Global Renewables Outlook; c) Linkedin 'green' skills; d) SGG Singapore green economy skills; e) JRC GreenComp framework; f) O*NET green skills taxonomy g) ESCO green skills taxonomy. This produced an initial list of 140 green terms. In the second step, 6 million OJAs containing the green terms were extracted from Eurostat's WIH. The corpus of these OJAs was used to generate a word embedding, which was used to enrich the initial list of green terms with lexicon variations. The enhanced list of 182 extracted terms in English was then translated and validated by national experts for all languages in the WIH and used for ontology-based extraction. Using cosine similarity, each green skills term was associated with the ESCO green skills taxonomy. Where no such association existed, the term was added as a new green skill term.

C Jaccard Distances distribution

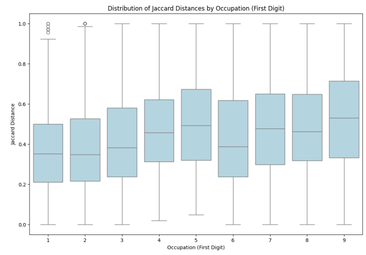
Figure 6: Jaccard Distance: overall distribution by Year, Country, and 1Digit Occupation



(a) JD distribution by Year



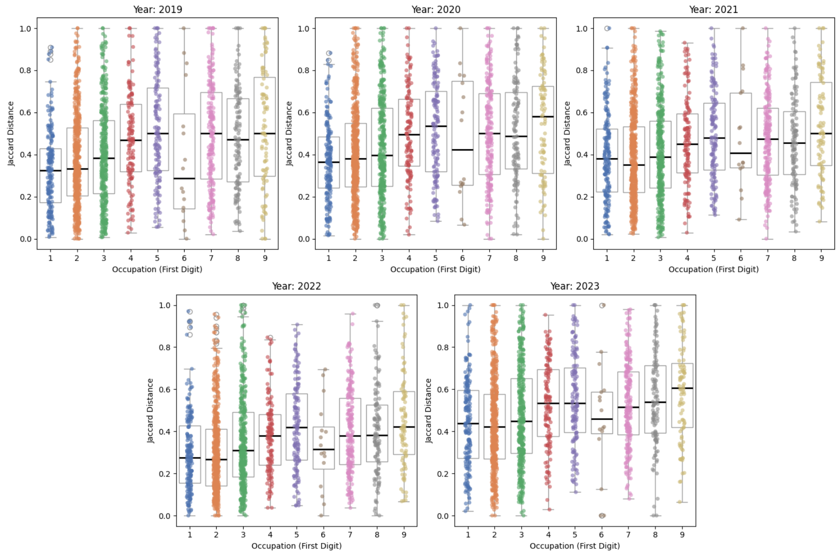
(b) JD distribution by Country



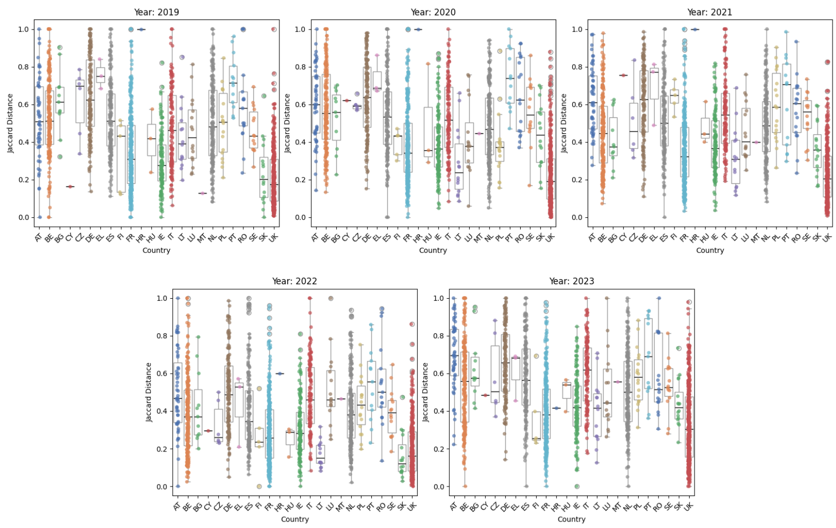
(c) JD Distribution by 1Digit ESCO

Note: authors' calculations on WIH-OJA data

Figure 7: Jaccard Distance: distribution by Year for Country, and 1Digit Occupation



(a) JD distribution by 1Digit in 2018-2023



(b) JD distribution by Year and Country

Note: authors' calculations on WIH-OJA data

D OECD Greenness Index: Details

D.1 Descriptive statistics

Table 13: Summary Statistics for Greenness by Green OJA

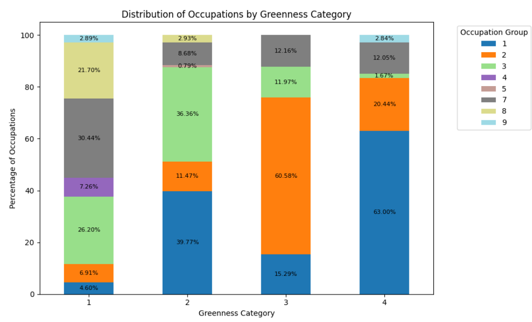
Green OJA	Mean	SD	Min	Max
0	0.0403011	0.1085415	0	1
1	0.0722942	0.1507054	0	1
Total	0.0418543	0.1111719	0	1

D.1.1 Statistics by Greenness Quartiles

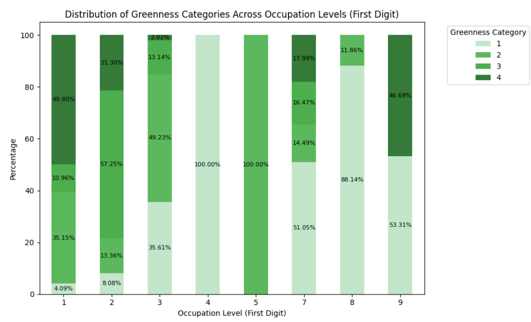
Table 14: Distribution of Greenness Quantiles

OECD Greenness Quartiles	Frequency	Percent	Cumulative
1	2,012,167	27.07	27.07
2	2,003,910	26.96	54.03
3	1,625,019	21.86	75.89
4	1,792,052	24.11	100.00
Total	**7,433,148**	**100.00**	

Figure 8: Composition of Greenness Quartiles



(a) 1Digit Occupation by Greenness Quartiles

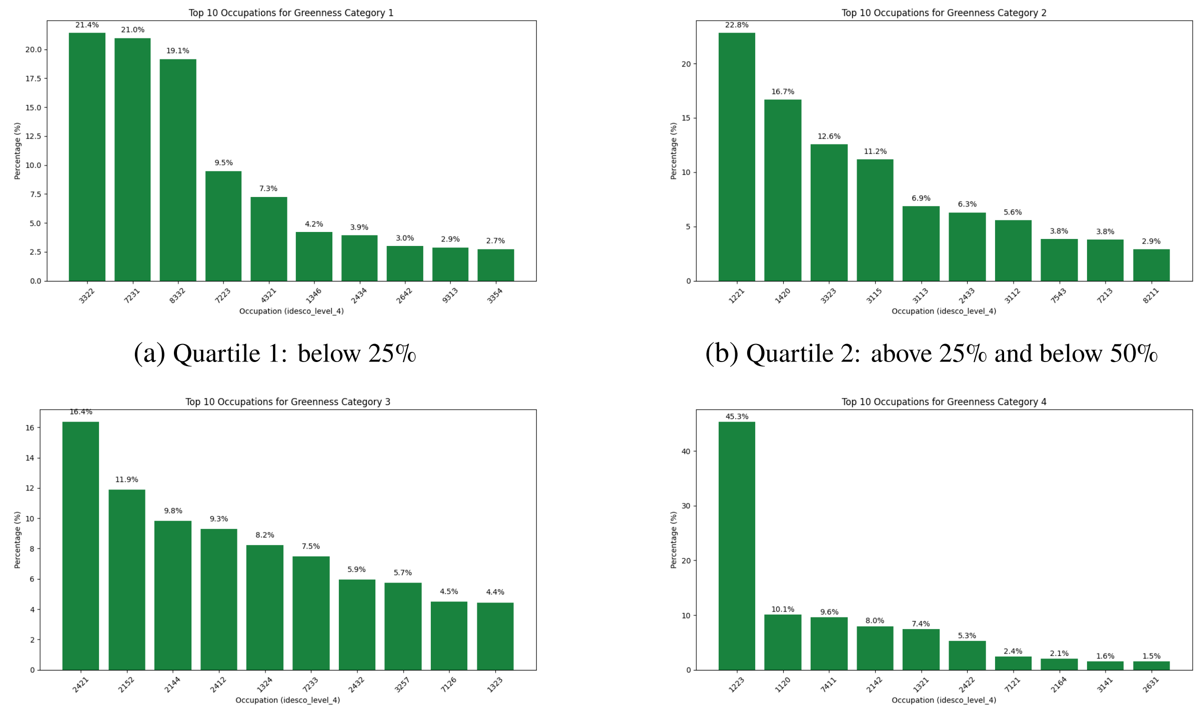


(b) Greenness Categories across 1D occupations

Note: authors' calculations on WIH-OJA data

The occupations characterized by the greenness distribution quartiles, as shown in Figure 8, reveal distinct patterns across categories. In Category 1 (below 25%), occupations such as buyers (3323), commercial sales representatives (3322), and motor vehicle mechanics and repairers (7231) dominate. Category 2 (above 25% and below 50%) includes more managerial positions such as research and development managers (1223) and retail and wholesale trade managers (1420). In Category 3 (above 50% and below 75%), occupations like management

Figure 9: Top 10 ESCO Occupations by Greenness Quartile



(a) Quartile 1: below 25%

(b) Quartile 2: above 25% and below 50%

(c) Quartile 3: above 50% and below 75%

(d) Quartile 4: above 75%

Note: authors' calculations on WIH-OJA data

and organization analysts (2421) and electronics engineers (2152) begin to appear more frequently, indicating a shift toward technical and analytical roles with stronger connections to sustainability. Finally, Category 4 (above 75%) is dominated by sales and marketing managers (1221) and research and development managers (1223), highlighting occupations that usually require higher education. These distributions suggest that higher greenness quartiles are characterized by increasing specialization, managerial oversight, and innovation-oriented roles. In contrast, lower quartiles are predominantly associated with operational and sales-focused occupations.