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

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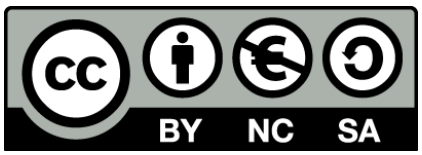

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Let's get green: understanding green skills and jobs through online job advertisements*

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Abstract

Green jobs and skills are pivotal to global and European efforts toward an environmentally sustainable economy and climate neutrality. Understanding their characteristics is essential for designing effective policies to address workforce challenges during this transition. While existing literature typically identifies green jobs using occupational proxies—by classifying entire occupations as green or assigning greenness scores based on task content (e.g., Bowen et al. (2018); Vona et al. (2019))—this study advances the analysis by focusing directly on green skills, using data from Eurostat's Web Intelligence Hub on Online Job Advertisements (OJAs). This dataset provides job-level information on skill requirements, revealing substantial within-occupation heterogeneity. We define green OJAs as postings that mention at least one green skill and analyze them at the ISCO 4-digit level across 26 European countries from 2019 to 2023. Our findings show that green OJAs are associated with higher education requirements, higher offered wages, and lower experience demands compared to non-green postings. Moreover, by introducing an occupation greenness score, we find that green OJAs in brown occupations—those with no task-based greenness—also command a wage premium, suggesting that green skills are valued independently of occupational context. The granularity of the data allows us to explore differences in skill demand at both the extensive and intensive margins. Green OJAs emphasize social, communication, and management skills, and also require more specialized cognitive and manual skills, reflecting the hybrid and context-specific nature of green work.

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 has dedicated €1 trillion towards sustainable investments by the year 2030, utilizing Next Generation EU and the EU's seven-year budget. The execution has been strengthened by major EU initiatives, including the European Year of Skills set for 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). Evidence from EU countries shows that climate policies might be skill-biased, with stronger positive effects on high-skilled workers—especially technicians and professionals—while manual workers face employment losses, highlighting the need for re-skilling strategies (Marin and Vona, 2019). 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 correspond to green occupations; our approach enables an analysis *within* an occupation, distinguishing between OJAs that contain green skills and those that don't.

This framework does not conflict with the task 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. While most of the existing literature on green jobs relies on U.S. data, only a few studies have explored the European context. Connolly et al. (2016) and Sulich and Soloducho-Pelc (2022) use top-down employment statistics, such as sector-level data from Eurostat or national sources, to estimate green employment, focusing on broad sectoral trends rather than occupational detail. Sulich et al. (2020) similarly examines the role of green jobs in addressing youth unemployment using aggregated employment data. More recently, Elliott et al. (2024) apply a task-based approach to Dutch administrative data by linking ONET's green tasks to ISCO-coded occupations through a crosswalk, enabling firm-level analysis of green employment composition. However, their focus remains at the occupational level rather than at the skill level. 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 the 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 around 1,000 sources throughout Europe, encompassing major public and private entities within the online labor market, such as specialized job boards, public employment services, websites of private employment agencies,

and job sections of national newspapers. These OJAs are downloaded and analyzed to extract key information, including job title, job description, geographic location, the economic sector of the employer, and required skills (Cedefop, 2019). The information extracted is utilized to classify the data based on the European Union's official taxonomy, namely the European System of Skills, Competences, Qualifications, and Occupations (ESCO), reaching the 4th level of the International Standard Classification of Occupations (ISCO). In addition, various other elements of OJAs are extracted and classified in accordance with major international standards: location (NUTS), education (ISCED Levels),[1] economic activity (NACE Rev.2 Divisions), and skills (ESCO skill concepts). More specifically, skill categorization relies on the ESCO Skills pillar taxonomy. This taxonomy serves as a reference dictionary, comprising nearly 14,000 distinct skills, with skill names and synonyms acting as inputs for a classifier.[2] Using the ESCO taxonomy we are able to extract approximately 3000 skills in the text contained in OJAs; given the large number of skills identified in the data, we present a broad classification that differentiates between Cognitive, Digital, Manual, Management, Social, and Communication skills (refer to Table 9 for more information).

Information on the level of experience is recorded on an 8-point scale as detailed in Table 12, while wage data is reported a 13-point scale corresponding to the wage bands defined in Table 11.

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.

Due to the general absence of wage details in most OJAs, relying on wage data significantly narrows the sample size. However, this does not pose a problem for our analysis for three reasons. Firstly, even with this limitation, we still have nearly 30 million observations, representing 10% of the entire dataset, which is sufficient for a comprehensive analysis. Secondly, since our analysis is performed *within* specific detailed occupations, the risk of sample selection bias is minimized. Lastly, the findings pertaining to other variables such as education and experience in a larger dataset are consistent with those from the subset that includes wage data.[3]

[1] For a detailed classification, refer to table 10

[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: professional, transversal, and digital skills.

[3] Results available upon request.

2.1 Green skills, green jobs and green OJAs

There is a substantial amount of research investigating the notion of green jobs, yet a universally acknowledged definition continues to be 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 analyse the type of product or the technology employed in production.

The second approach begins with the examination and classification of specific occupations into green or non-green categories, termed as the occupation-specific approach. This method can be enhanced by evaluating the tasks within each occupation, transitioning from a simple green or non-green job dichotomy to a continuous metric that quantifies the extent of greenness in occupational activities. Under this approach, 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 how relevant green tasks are in each occupation (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)).[4]

2.1.1 Green jobs vs green OJA

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.

To better illustrate the nuances that our framework is able to capture, the box presents an example of two online job advertisements (OJAs) from our 2023 UK sample. Even though both job postings are for the identical specific role of a Civil Engineer (code 2142 of ESCO IV-digit classification), there is a significant variation in the skills required (emphasized in italics). Consequently, the first OJA is categorized as non-green because it lacks green skills, whereas the second one includes them.

[4] 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 (Nesta et al., 2014; Vona et al., 2018, 2019).

Occupation: Civil Engineer

- **OJA A: Civil Engineering Apprentice (Not Green)**
  We are looking for a talented and enthusiastic apprentice to join the Civil Engineering team. We work together to deliver highway and drainage designs, cut fill analysis and much more. We use the leading industry modelling software to build cutting edge designs delivering maximum value for our clients. Within this role you will be entrusted to undertake various tasks to support the design team. Civil Engineering requires excellent *problem solving and analytical skills* and you will be encouraged to think outside the box from the very beginning. Within your role you will be given full training and support to develop design and drafting skills you will continue to expand throughout your career. You will be encouraged to join engineers on site, to observe the construction of designs and meet with adopting authorities and clients and to gain a wider understanding of the construction process. Requirements include: a good standard of *maths and written communication, good ICT skills, an interest in AutoCAD or computer-aided design, and the ability to manage your workload efficiently*.
- **OJA B: Flood Risk Engineer (Green)**
  Due to the increased risk of flooding and the Council's recent declaration of a climate emergency, we look for a Civil Engineer, with a focus on flood risk, to *support development planning and flood risk management in line with relevant legislation,* including the duties of the Lead Local Flood Authority under the Flood and Water Management Act.

  The role involves supporting *strategic flood risk activities, attending countywide meetings, and operating the Council's flood reporting database*. The engineer must assess and manage features that significantly affect flood risk and carry out responsibilities such as investigating flood incidents and overseeing consenting and enforcement work related to ordinary watercourses. The position also includes contributing to the preparation of new legislation and arrangements for the *adoption and maintenance of sustainable drainage systems (SuDS)*.

The text is from the original job advertisement. Words in italic identify the extracted skills.

Therefore the key feature of our approach is that 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 for workers to complete such tasks, i.e., skills requested by employers in job postings for such positions.[5] Moreover, by focusing on the skill content of jobs, we address one of the main criticisms of the task-based method, which is that even 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.

2.1.2 Green skills

Since our identification of green OJAs is based on the analysis of their skill requirements, the definition of green skills plays a central role in our approach. We adopt the green skills tax-

[5] 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).

onomy developed by Eurostat, which integrates methodologies from both ESCO and Cedefop. Specifically, a skill is classified as green if it meets two criteria. First, it must be included in the ESCO Green Skills group (ESCO Publications, 2022).[6] Second, the classification is augmented using a set of green terms identified by Cedefop (Cedefop, 2024), which capture additional relevant competencies not explicitly listed in ESCO.[7]

The outcome of this procedure is a data-driven taxonomy that enhances the standard ESCO classification by incorporating a broader and more dynamic set of skills aligned with environmental objectives. To provide some examples, the set of terms used includes: *advise on offshore renewable energies subjects*, *develop flood remediation strategies*, *use sustainable materials and components*, *coordinate waste management procedures*, *conduct environmental surveys*, *identify energy needs*, *geothermal power generation methods*

2.1.3 Green jobs

As stressed above, the main focus of our analysis is conducted within occupations distinguishing green from non-green OJAs; however, to deepen the analysis and to compare it with the literature, we will also distinguish between green and non-green occupations by employing the OECD Greeness measure (Scholl et al., 2023) which assigns a "green' value to each ISCO-08 IV digit occupation.[8]

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.

[6]The report explains how green skills are identified through a three-step process combining manual labelling, machine learning classification, and final validation. The complete list of ESCO Green skills can be downloaded from ESCO together with the whole Skill Taxonomy.

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

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

2.2 Descriptive statistics

The final dataset comprises 26 Countries,[9] 353 ISCO Occupations and 29,236,393 unique OJAs, of which 1,419,207 (5%) are classified as green.

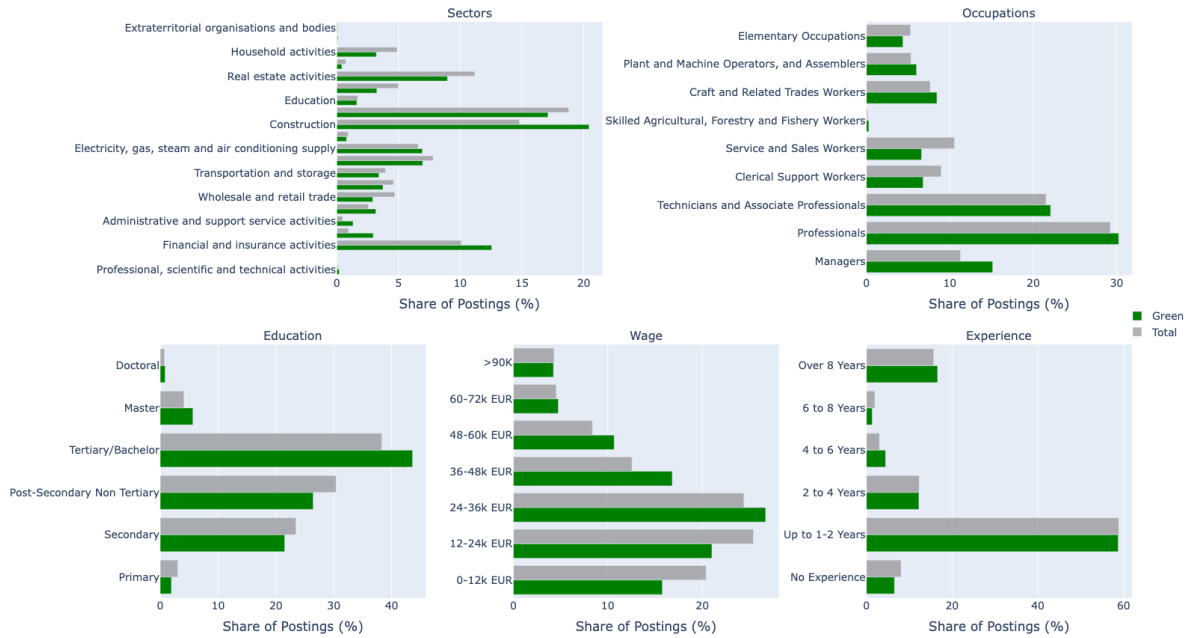
As shown in Figure 1, the distributions for green and non-green OJAs highlight some general features of green jobs. Green OJAs are more concentrated in professional, scientific, and technical activities (M), manufacturing (C), energy supply (D), water supply and sewage management (E), construction (F) 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.[10] 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 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).[11]

[9] This includes all EU countries plus the UK and minus Estonia and Lithuania excluded due to the low number of observations.

[10] 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 12, 11, and 10.

[11] Compared to the actual employment distribution in Europe, the distribution of Online Job Advertisements (OJAs) is skewed toward high-skill occupations. This overrepresentation arises from the higher likelihood that high-skill positions are advertised online relative to low-skill ones. Importantly, this sampling characteristic does not bias our analysis: there is neither theoretical justification nor empirical evidence to suggest that green job advertisements follow systematically different online posting patterns compared to non-green positions.

Figure 1: Distribution of Green vs Total Online Job Ads Across Job Characteristics



Note: authors' calculations on WIH-OJA data. The horizontal bars represent the share of green and Total OJA for each category.

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 similar to Consoli et al. (2016) and summarised by the following equation:

$$y_{i,c,s,t} = \alpha + \beta \text{ Green}_{i,c,s,t} + \gamma_i + \delta_c + \theta_s + \lambda_t + \epsilon_{i,c,s,t} \quad (1)$$

Where the dependent variable is in turn education, experience, and wage; $Green$ is the variable of interest and is a dummy variable indicating if the OJA contains at least one green skill (1) or not (0) and therefore if it is classified as green. The regression is saturated with fixed effects for IV digit occupation (γ_i), country (δ_c), sector (θ_s), and year (λ_t).

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 years, 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.

It is important to note that the results presented in the main text are based on OLS regressions, which may not be fully appropriate given that the dependent variable is categorical rather than continuous. A more appropriate candidate model would be an ordered logit. Our choice is motivated by practical considerations. Specifically, estimating nonlinear models such as ordered logit in high-dimensional panel settings, like the one used in this study, involves maximizing complex log-likelihood functions, which is computationally very intensive. However, to assess the robustness of our results—and, more importantly, to interpret the implied odds ratios—we estimate an ordered logit model on a representative sample of 1.5 million observations. The results of this specification are fully consistent with those of the main analysis, supporting the validity of our approach. Further details are provided in Appendix D.

The magnitude of the estimated coefficients may appear modest compared to findings in the rest of the literature. However, it is important to emphasize that our estimates are identified *within* detailed occupational groups, whereas most existing studies estimate effects

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.

across occupations. To revisit the earlier example, our analysis is akin to comparing two civil engineers working in the same country, sector, and year, where the primary difference lies in their skill requirements. Given the narrow scope of analysis, large effect sizes are not expected.

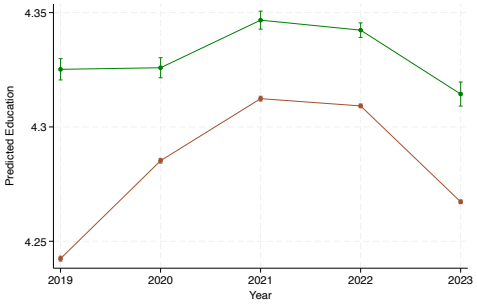
However, estimated coefficients are not as small as they appear. The analysis presented in Appendix D, based on a representative sample and estimated using an Ordered Logit model, provides odds ratios (Table 18) that quantify the association between green skills and job requirements. The results indicate that OJAs mentioning green skills are associated with 10.9% and 17.2% higher odds of requiring a higher education and wage category, respectively, and with 2.4% lower odds of falling into a lower experience category, compared to OJAs without green skills, holding other factors constant.

3.2 Profiling of green OJAs over time

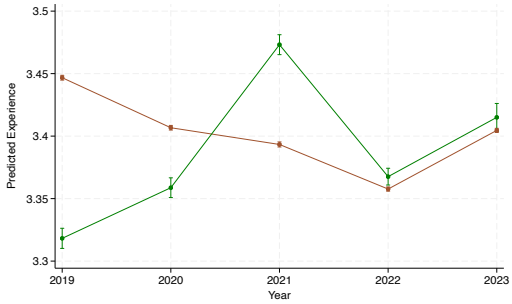
Albeit our data does not provide long time series, it is worth analyzing whether the evidence collected above is stable over time. This is done by interacting the green dummy with a time index. Figure 2 plots the estimated coefficients. Overall, the general message is that the education and wage premium carried by green skills holds irrespective of the time period. Note

that the wage premium is considerably reduced in 2020 and 2021. This can be explained by 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 align.

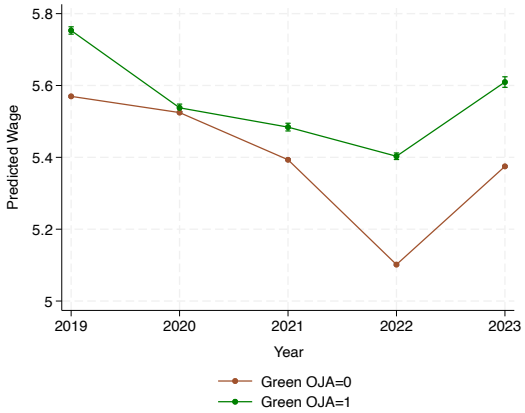
Figure 2: Interaction effects: Time variable with Green OJA Dummy



(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 classifies online job advertisements (OJAs) into two categories—green and non-green—using a binary indicator that dichotomizes the degree of greenness. However, it is worth noting that some OJAs include more than one green skill, suggesting variation in the intensity of green content. This raises the question of whether our results also capture the *intensive margin* of greenness, beyond the simple binary distinction. In Table 3, we replace the binary green indicator with two alternative measures to capture the intensive margin of greenness in job postings. The first is the percentage of green skills in an OJA, calculated as the share of green skills relative to the total number of skills listed. This measure reflects the intuition that a higher concentration of green skills better identifies postings where green competencies are central, rather than peripheral, to the job profile. The second measure is a simple count of green skills, which shifts the focus to the absolute number of green competencies required, regardless of their share among the total.

Together, these indicators allow us to assess whether the degree of greenness—both in relative and absolute terms—is associated with variation in job requirements. 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. In this section, 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 detailed information provided by the O*NET database for the United States, define the Greenness of an occupation as the

share of green-specific tasks relative to the total number of specific tasks associated with that occupation. The OECD measure is built by mapping indicators originally developed for the U.S. Standard Occupational Classification (SOC) system onto the International Standard Classification of Occupations (ISCO-08) used in Europe, at the detailed 4-digit occupational level.

Green OJAs and green occupations are clearly related: the mean greenness is significantly higher for OJAs containing green skills.[12] Appendix C provides some descriptive statistics of the distribution of green occupations in our sample.

The introduction of green occupations enables a more detailed investigation of the characteristics of green OJAs, specifically whether these features are concentrated within green occupations or extend across the broader occupational spectrum.

We begin by distinguishing between green and brown occupations: the former are those assigned a positive greenness score by the OECD, while the latter include all remaining occupations. To investigate the transversal nature of green skills, we initially focus 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 and by Bluedorn et al. (2023) for a cross section of countries. Interestingly, the interaction term reveals that the premium for green skills is stronger in brown occupations. This suggests that green skills required by the OJA carry significant value, particularly in roles not explicitly classified as green. This finding highlights the broad relevance of green skills, which are valued across the labor market and rewarded even in non-green occupations.

Next, we focus on the restricted sample of green occupations (Tables 5 and 6).[13]

The overall effect for the green OJA indicator is confirmed. However, the greeness effect 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. When considering only OJAs without green skills, those associated with occupations of higher greenness tend to require higher education but lower experience and offer lower wages. However, the interaction term reveals that the presence of green skills in the OJA is associated with a premium in both education and experience requirements, while

[12] As confirmed by a two-sample t-test (mean difference = 0.032, $t = -340$, $p < 0.001$)

[13] 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 $\times$ 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.

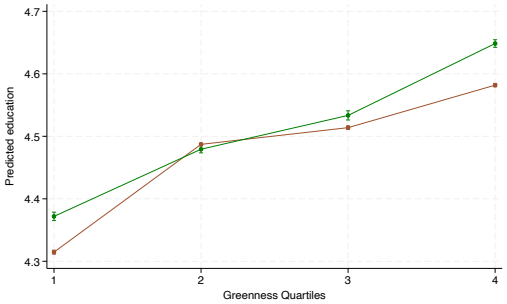
the wage effect is negative. To further investigate these dynamics, we divide the greenness index into quartiles and analyze the marginal effects at different levels of greenness, focusing on how they interact with the presence of green skills in the OJA.

Results are shown in Table 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 Figure 3. One possible explanation for this pattern is that green know-how is increasingly seen as a standard requirement within green occupations—especially as the degree of greenness rises. In highly green occupations, where tasks are likely more standardized, the wage gap between green and brown OJAs narrows, reflecting a lower premium for green skills. Additionally, occupational composition within greenness quartiles likely contributes to these effects. Quartiles Q1 and Q4 are more polarized: Q4 is dominated by high-skilled occupations, while Q1 includes mostly elementary ones. In contrast, Q2 and Q3 encompass a broader and more heterogeneous mix of occupations across the ISCO-08 classification (see Figure 6 in appendix C).

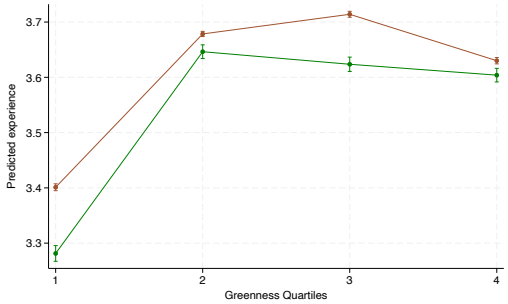
4 Analysing green-jobs skill bundles

The analysis so far provides robust evidence that green job opportunities constitute a segment of labor market demand associated with higher wages, targeting candidates with higher educational attainment and shorter prior work experience. In this context, it becomes essential to examine the skill profile of green OJAs to better understand the specific skill mix they require compared to non-green roles. Previous contributions on this topic are framed within the task-based approach. In such a framework, the identification of green occupations is mediated by the identification of the green tasks they are required to perform. Once the occupation is assigned a greenness score, skills connected to these occupations are collected and analysed (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)). However, as explained in section 2.1 our approach diverges from the existing literature by focusing on the skills demanded in green jobs, rather than on the activities performed in green occupations.

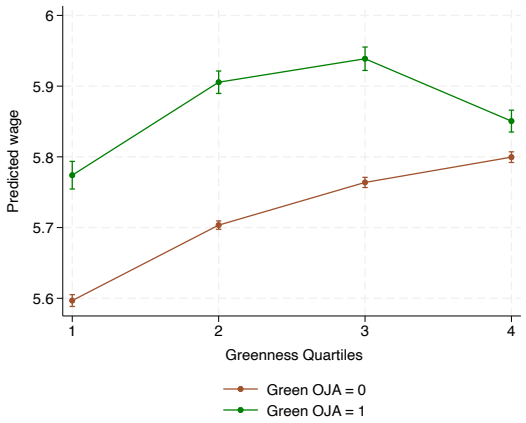
Figure 3: Interaction Effects: Green OJA and Greenness Quartiles on Human Capital variables



(a) Greenness Quartiles and Education



(b) Greenness Quartiles and Experience



(c) Greenness Quartiles and Wage

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.

Shifting to the analysis of skills, the available evidence is much scarcer. Vona et al. (2018) highlight two key sets of green skills that characterise green occupations: engineering skills for designing and producing green technologies, and managerial skills for implementing and overseeing environmental organizational practices.

In this section, we leverage information on skill sets reported in OJAs to analyze the variety and specialization of green job opportunities. Specifically, we exclude green skills from green OJAs and compare the residual skill bundle with that of non-green OJAs. The analysis focuses on the demand for key skill categories—cognitive, social and communication, digital, manual, and managerial—to assess whether green job postings differ in their broader skill profiles beyond their environmental content. The analysis is structured along two main dimensions, each capturing distinct aspects of skill requirements. First, in Section 4.1, we examine differences in the *variety of skill bundles*, highlighting which skill types drive the divergence and overlap in skill sets within occupations. Second, in Section 4.2, we focus on the *specialization of skill requirements* in green job opportunities compared to non-green ones, aiming to identify which skill groups are most distinctive of green occupations.

Table 7: Average Number of Skills per Group, by Green and Non-Green OJAs

OJA Type	Cognitive	Digital	Management	Manual	Soc. & Comm.	Total
Non-Green (0)	0.67	1.29	3.91	0.29	3.94	10.10
Green (1)	0.89	1.46	4.38	0.36	4.24	11.33

Note: Authors' calculations based on WIH-OJA data. Each value represents the average number of skills per skill group across green and non-green job ads.

To set the stage, Table 7 reports the average number of skills listed in green and non-green OJAs. Overall, the two groups exhibit a similar total number of skills, as well as a comparable distribution across skill categories. In both green and non-green postings, management and social and communication skills have the highest average counts, suggesting their central role in job requirements regardless of environmental content.

4.1 Variety of the skill bundle

The first dimension of interest is skill variety, which captures the richness of the skill portfolio demanded by recruiters. Assessing the degree of overlap between the skill sets of green and non-green job opportunities helps determine whether work involving environmentally sustainable competencies is performed in a uniform way compared to jobs that do not require such skills.

We construct a measure of similarity between skill sets, computing the Jaccard distance

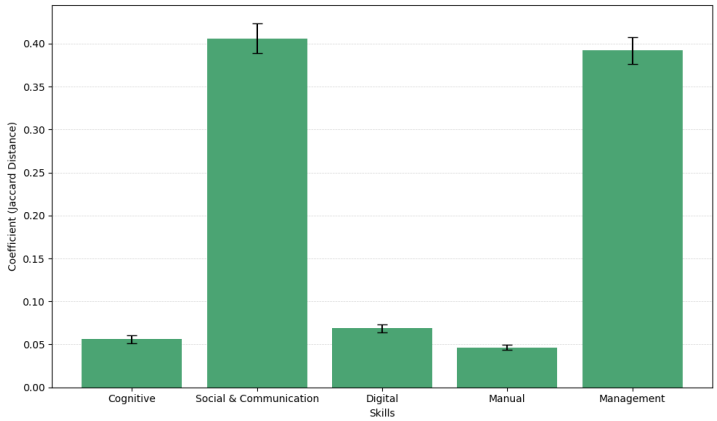
between the skill requirements of green OJA compared with non-green OJAs within the same occupational code (ISCO-08 IV digit), defined as follows:

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

where i represents the occupation, g represents the subset of green OJAs, and ng represents non-green ones. $S_{(i,g)}$ denotes the set of skills associated with the green OJA for occupation i, and $S_{(i,ng)}$ denotes the set of skills in 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 E, we examine the overall distribution of Jaccard distances across years, countries, and occupational groups. The evidence presented in Figure 8a also highlights a positive relation between overlap in skill requirements and the ranking in the occupational hierarchy. Green managerial OJAs share around 60% of their skill sets with their non-green counterparts, while only 40% of skill requirements in elementary occupations are common to green and non-green job opportunities within the same occupational group. The trend appears generally stable over time.

Figure 4: Composition of Jaccard Distance



Note: authors' calculations on WIH-OJA data. The bars report the values and standard errors of a constrained regression of the overall Jaccard distance on each component considering country, sector, year and occupation fixed effects.

Following the definition given in equation (2), we computed the Jaccard distance in the skill bundle at occupation level between green and non-green OJAs. We have grouped the skills into 5 different mutually exclusive and exhaustive classes: Cognitive skills, Social and communication skills, Digital skills, Manual skills, Management skills, using the ESCO

taxonomy as described above. Under the condition of skills belonging to one and only one of the mutually exclusive skill groups, the overall Jaccard distance has the property of additivity, meaning that it is the sum of the distances for all different skill types.

Figure 4 presents the coefficients from a constrained regression of the overall Jaccard distance on the five group-specific Jaccard distances, controlling for occupation, country, and year fixed effects. This specification leverages the additive structure of the Jaccard index to quantify the marginal contribution of each skill category to the overall divergence in skill requirements between green and non-green jobs.[14] The results indicate that differences in management and social and communication skills account for the largest shares of this divergence, with estimated coefficients of 0.39 and 0.40, respectively. The contributions of *cognitive*, *digital*, and *manual* skills are substantially smaller. These findings underscore the central role of higher-order interpersonal and organizational skills in the green transition.

4.2 Skill specialization of green jobs

Variety measures the scope and diversity of skills required to perform green jobs compared to non-green ones. However, this indicator does not capture the importance or intensity of specific skills within the job profile. To address this limitation, we introduce a measure of specialization, which reflects the relative intensity of skill demand. This allows us to compare how prominently different skill groups feature in green versus non-green job postings. For this purpose, we adopt a well-established metric in the literature—the location quotient, also known as Revealed Comparative Advantage (RCA). 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 approach, 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 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

[14] The constrained regression allows to estimate shares while taking into account detailed fixed effects.

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). The RSCA has been computed for each skill and subsequently grouped following the skill taxonomy developed in the previous section. In this way, it is possible to assess the specialization of OJAs for each skill category.

Our results, presented in Table 8, indicate that green OJAs exhibit a higher degree of job-specific and less common skill sets compared to non-green counterparts. In particular, cognitive and manual skills are the main drivers of specialization in green OJAs. By contrast, digital and managerial skills appear to be more widely shared across both green and non-green job postings, suggesting they are more transversal in nature.

The distinction between cognitive and manual skills highlights the unique demands of green jobs, where workers are often required to combine specialized problem-solving abilities with practical, hands-on expertise. In contrast, the widespread presence of digital and managerial skills across both green and non-green occupations likely reflects broader labor market trends—namely, increasing digitization and the rising relevance of managerial competencies

Table 8: 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.

across a wide range of sectors, not limited to environmentally focused roles. This finding is consistent with part of the existing literature, such as 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. We find that the difference in skill requirement between green and non-green OJAs is present even within occupations. 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

The task-based literature has shed light on which components of job activities are relevant to green processes, offering valuable insights into their functional relevance within occupations. 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, with green jobs differing markedly from non-green jobs—even within narrowly defined occupational categories. Specifically, green jobs tend to require higher levels of education, while employers appear to prefer less experienced candidates, possibly due to the specificity and evolving nature of green production processes. Most notably, we find a significant wage premium associated with green skills, underscoring the market value attributed to environmental 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, indicating that it is the presence of green competencies—rather than the occupation itself—that drives higher job requirements and remuneration. Moreover, 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 observed differences in skill bundles are largely driven by social, communication,

and managerial skills—components of a broader portfolio that supports workers' integration into organizational structures and their ability to confidently lead or coordinate processes. Most importantly, what makes the profiles of green jobs truly unique is the presence of two additional sets of skills: cognitive and manual. This combination suggests that workers in green roles are expected to operate simultaneously at the level of analytical thinking and planning, while also being proficient in hands-on, practical tasks. The coexistence of these skill demands reflects the idiosyncratic nature of the strategies and solutions that organizations adopt to achieve their green objectives, often requiring tailored approaches that blend conceptual understanding with operational execution.

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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Appendix

A Mappings

Table 9: 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 10: 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 11: 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 12: 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 13: 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 Skills Taxonomy has been obtained using a data-driven framework designed to classify and analyse skills relevant to the green transition. It enhances and integrates several existing frameworks through a multi-step, bottom-up methodology. In the *first phase*, Cedefop compiled a "bag of green-related words" encompassing terms associated with green technologies, environmental tasks, tools, and competencies. This lexicon was developed from several authoritative sources, including the UN System of Environmental Economic Accounting (CEPA and CReMA classifications), the IRENA Global Renewables Outlook, LinkedIn's list of green skills, the SGG Singapore Green Economy Skills Framework, the European Commission's JRC GreenComp Framework, the U.S. O*NET Green Skills Taxonomy, and the ESCO Green Skills Taxonomy. This produced an initial list of 140 green terms in English, covering topics such as *solar energy*, *biodiversity*, *energy consumption maintenance*, and *corporate social responsibility*.

In the *second phase*, over 6 million online job advertisements (OJAs) collected by Eurostat through the WIH-OJA (Web Intelligence Hub – Online Job Advertisements) system in 2019

were used as a corpus to train a word embedding model. The model expanded the original list by identifying semantically similar terms and lexical variations, leading to an enhanced vocabulary of 182 validated green skill terms. These were then translated and validated by national experts in all WIH-OJA system languages. The enriched terms include examples like *green computing*, *ecosystems*, *environmental engineering*, *circular economy*, *hydroelectricity*, and *combined heat and power generation*.

In the final step, each term was mapped to the ESCO Green Skills Taxonomy using cosine similarity. Where no suitable match existed, the term was added as a new entry, allowing the taxonomy to remain responsive to emerging labour market trends and technologies. For further information, see Cedefop (2024).

C OECD Greenness Index: Details

C.1 Descriptive statistics

Table 14: 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

C.1.1 Statistics by Greenness Quartiles

Table 15 reports the distribution of online job advertisements (OJAs) across the four greenness quartiles based on the OECD greenness index.

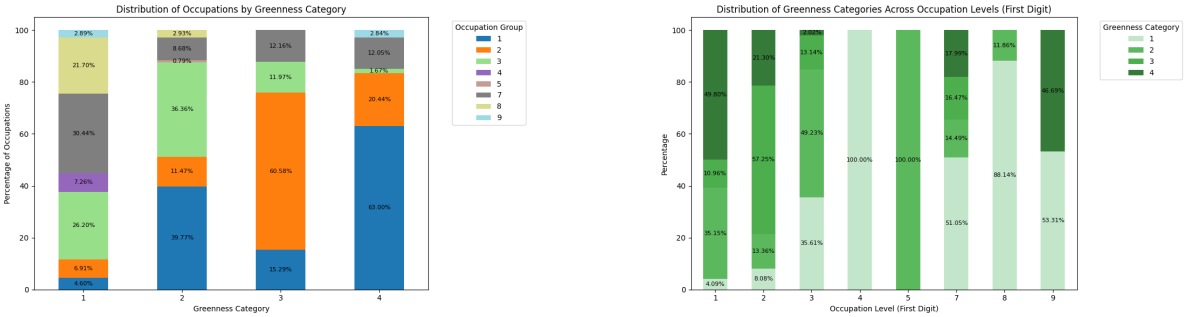
Table 15: Distribution of Greenness Quantiles

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**	

The data are relatively balanced, with each quartile representing approximately one-quarter of the total sample: 27% of the observations fall into Quartile 1 (lowest greenness), 27% into Quartile 2, 22% into Quartile 3, and 24% into Quartile 4 (highest greenness). This even split provides a solid basis for comparing job characteristics across the greenness spectrum.

Figure 5 offers an overview of how occupational categories differ by greenness level.

Figure 5: Composition of Greenness Quartiles



(a) 1Digit Occupation by Greenness Quartiles

(b) Greenness Categories across 1D occupations

Note: authors' calculations on WIH-OJA data

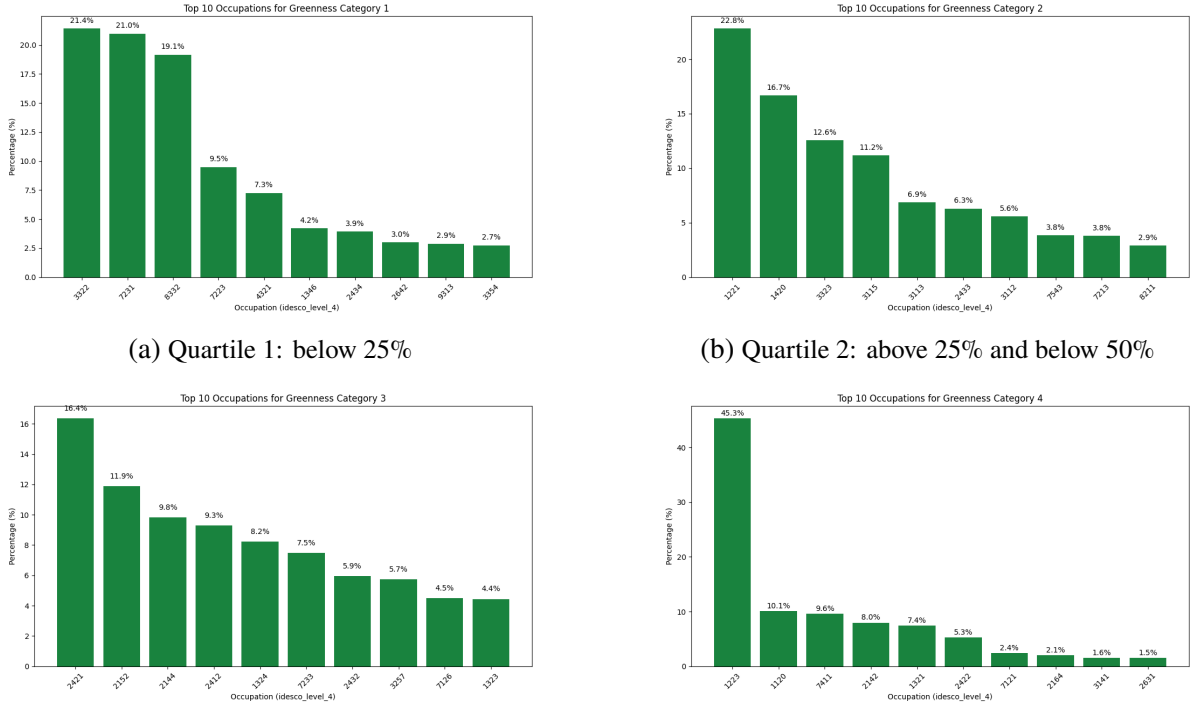
Panel (a) presents the distribution of 1-digit ISCO occupations by greenness quartile, revealing that lower quartiles are primarily composed of service, sales, and manual roles. In contrast, higher quartiles show a notable shift toward professional and managerial occupations, indicating increasing complexity and skill requirements as greenness rises. Panel (b) further illustrates this pattern by displaying the proportion of each major ISCO group within each quartile. Managers (ISCO 1) and Professionals (ISCO 2) are increasingly prevalent in quartiles 3 and 4, reinforcing the link between greener job content and more advanced occupational categories.

Figure 6 provides a more granular look at the top ten ESCO occupations within each greenness quartile. In quartile 1 (below the 25th percentile), occupations such as buyers (3323), commercial sales representatives (3322), and motor vehicle mechanics and repairers (7231) are the most common, reflecting operational and routine service tasks. Quartile 2 (25th to 50th percentile) begins to include more managerial roles like research and development managers (1223) and retail and wholesale trade managers (1420). As greenness increases further in Quartile 3 (50th to 75th percentile), technical and analytical occupations such as organization analysts (2421) and electronics engineers (2152) become more frequent, reflecting a stronger connection to sustainability-focused tasks. Finally, quartile 4 (above the 75th percentile) is dominated by occupations like sales and marketing managers (1221) and R&D managers (1223), roles typically associated with higher education levels and strategic responsibilities.

Overall, the figures suggest a clear gradient in occupational composition across greenness levels. Higher greenness quartiles are associated with increasing specialization, managerial oversight, and innovation-oriented tasks, whereas lower quartiles are more concentrated in routine, sales, and operational roles. This pattern aligns with our empirical findings, where

greener job ads tend to be linked with higher education and wages, and slightly less required experience.

Figure 6: 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

D Ordered logit Model

D.1 Sample extraction

To facilitate model estimation on a computationally manageable dataset while preserving the joint distribution of key categorical variables, we constructed a stratified random sample from the full dataset. Specifically, observations were grouped into strata defined by the cross-classification of `Green` status, year, country, macro-sector, and 4-digit ISCO occupation code. Within each stratum, approximately 5% of observations were randomly selected (rounded up to ensure at least one observation per cell). This proportional stratified sampling procedure ensures adequate representation of both common and rare subgroups—such as green jobs—across all dimensions, thereby reducing the risk of omitted category bias or model instability due to sparse cells, while substantially reducing the overall sample size for tractable estimation.

Table 16: Distribution of Green and Non-Green Jobs in Sample

Green	Frequency	Percent	Cumulative
0 (Non-Green)	1,468,332	92.51%	92.51%
1 (Green)	118,953	7.49%	100.00%
Total	1,587,285	100.00%	

Table 17: Summary Statistics of Observations per Stratification Cell

Variable	Obs	Mean	Std. Dev.	Min	Max
obs_per_cell	1,587,285	444.85	960.79	1	6,486

D.2 Estimates

We replicate the baseline model on the sample described above using an ordered logit specification which is more suitable to capture a categorical dependent variable. The results from the ordered logit regression, as shown in Table 18 are consistent with the OLS findings in Table 2: green OJAs are associated with higher education and salary levels, and slightly lower experience requirements. Odds ratios above 1 for education (1.109) and salary (1.172), and slightly below 1 for experience (0.976), mirror the direction and significance of the OLS coefficients. For comparison, Table 19 reports the OLS coefficients obtained on the restricted sample.

Table 18: Ordered Logit Regression Results for *Green OJA*: Coefficients and Odds Ratios

Model	(1) Education	(2) Experience	(3) Salary
Log-Odds Coefficients			
Green OJA	0.103***	−0.0242***	0.159***
	(0.00563)	(0.00564)	(0.00536)
Odds Ratios (Exponentiated Coefficients)			
Green OJA	1.109***	0.976***	1.172***
	(0.00625)	(0.00550)	(0.00628)
Observations	1,587,285	1,587,285	1,587,285

Standard errors in parentheses. Coefficients are from ordered logit regressions. Odds ratios are exponentiated coefficients. Base category: Green OJA = 0.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Regression Results: Education, Experience, and Salary- OLS on Sample

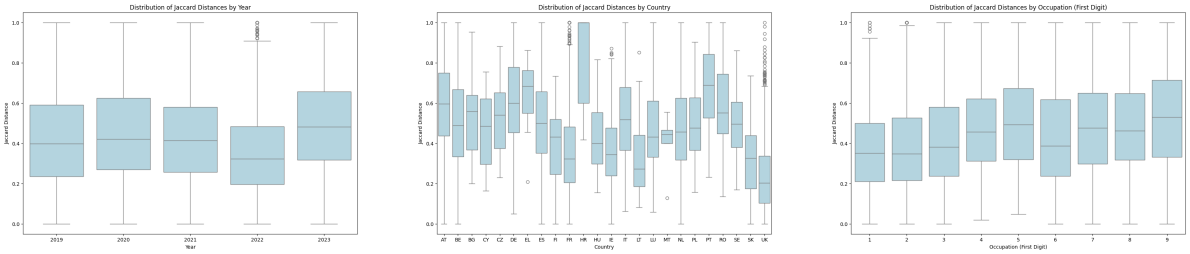
	(1) Education	**(2) Experience**	**(3) Salary**
GREEN OJA	0.0737^{***}	-0.0389^{***}	0.201^{***}
	(0.00364)	(0.00658)	(0.00920)
Education	–	0.0205^{***}	0.0680^{***}
		(0.00150)	(0.00212)
Experience	–	–	0.0868^{***}
			(0.00111)
Constant	4.290^{***}	3.316^{***}	4.765^{***}
	(0.00093)	(0.00670)	(0.0101)
Observations	1,587,282	1,587,282	1,587,282
R^2	0.271	0.066	0.150
Adj. R^2	0.270	0.066	0.150

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Jaccard Distances distribution

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



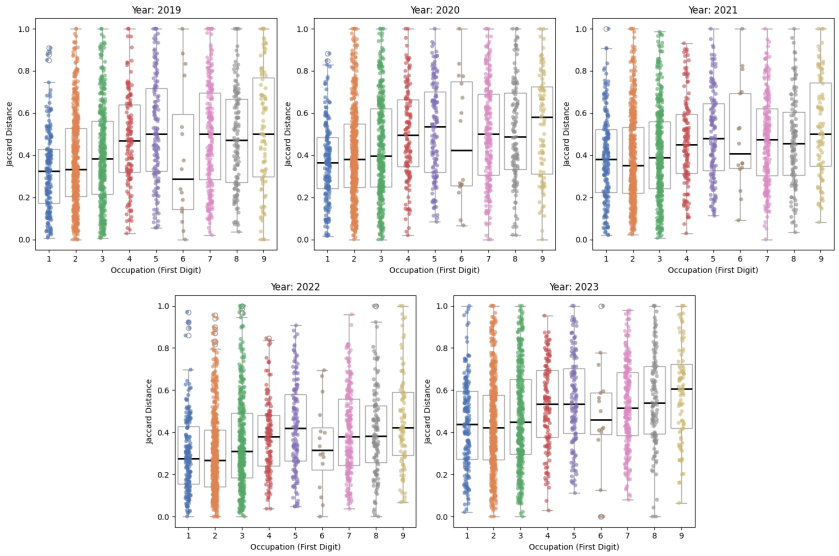
(a) JD distribution by Year

(b) JD distribution by Country

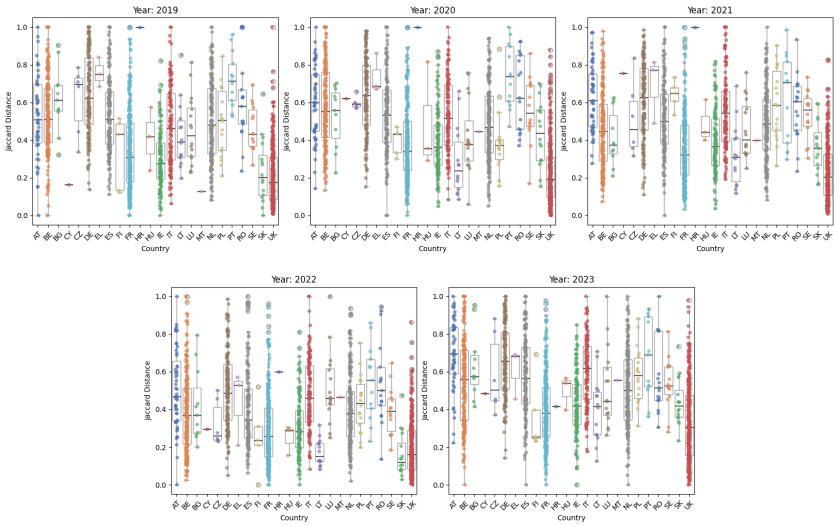
(c) JD Distribution by 1Digit ESCO

Note: authors' calculations on WIH-OJA data

Figure 8: 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