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Returns to Green Tasks in Europe: Evidence from Online Job Vacancies

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Abstract

There is growing evidence that green jobs have higher skill requirements, but whether they offer sufficient wage incentives to encourage workers to acquire those skills remains unclear. We study the green wage premium and its drivers to isolate the average return to green tasks using online job vacancy (OJV) data for EU countries over the period 2018-2023. We develop a transparent LLM-based approach to classify job vacancies as green when they list at least one green task. Green jobs pay a premium of 5.5% relative to comparable postings within the same occupation, and this estimate is little changed when controlling for nonmonetary job attributes making these jobs more attractive. Roughly half of this premium is explained by firm fixed effects, consistent with an important role for firm rents. An Oaxaca-Blinder decomposition shows that the higher skill complexity explains a further one tenth of the premium, leaving a residual return to green tasks of around 2%. The green wage premium is higher outside the manufacturing sector, and for low-carbon roles.

Keywords: Green wage premium, Skill gaps, Green tasks, LLM.
JEL: J24, J6, F64.

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1 Introduction

Public and policy debates increasingly frame the green transition as an opportunity for job creation or a threat for job destruction. Recent empirical work provides a more nuanced picture. On the one hand, it shows that the main issue is not simply how many jobs are created or destroyed, but which workers and places gain or lose, and under what conditions (e.g. Bachmann et al., 2026; Fabra et al., 2024; Hanson, 2023; Popp et al., 2021; Rud et al., 2024). On the other hand, a more established literature shows that the "job-killing" argument of environmental policies is overstated (Vona, 2019), largely restricted to pollution-intensive industries (e.g. Curtis, 2018; Greenstone, 2002; Kahn & Mansur, 2013; Marin et al., 2018; Walker, 2011) and muted in aggregate (Hafstead & Williams III, 2018; Metcalf & Stock, 2020; Yamazaki, 2017). Yet, despite growing attention to the employment effects of decarbonization, much less is known about the quality of green jobs - and in particular, whether the labour market generates sufficient wage incentives for workers to acquire the skills the transition demands.

This question matters beyond the green context. When a structural transformation - whether driven by trade, technology, or policy - creates demand for new tasks (Autor et al., 2003; Lin, 2011), the wage premium associated with those tasks signals the return to acquiring the corresponding skills (Autor & Handel, 2013; Deming, 2017). If the signal is strong, market forces can drive the required human capital investment and workers' reallocation towards the expanding occupations; if it is weak, policy intervention may be more needed to support such investments (Deming, 2022). In practice, however, observed wage premia for new tasks are difficult to isolate because they may reflect not only the return to performing the tasks themselves, but also correlated characteristics of the jobs, firms, or workers involved. Disentangling these components is essential for understanding whether labour markets alone can adjust to structural change.

We study this question in the context of the green transition. A growing literature estimates a "green wage premium" - the pay differential between green and non-green jobs -using occupation-level measures of greenness (Bluedorn et al., 2023; Kuai et al., 2025; Vona et al., 2019), firm-level classifications (Godøy & Isaksen, 2025; Krueger et al., 2023) or more recent vacancy-level approaches (Bone et al., 2025; Saussay et al., 2026). Estimates typically range from 4% to 10%. However, none of these estimates can cleanly separate the return to green tasks from other features of green work that are correlated with wages. For instance, occupational-level comparisons cannot separate green task content from other occupation-level attributes, since green and non-green jobs

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frequently coexist within the same occupation. Likewise, firm-level measures conflate task content with well-known firm-specific wage premia linked to rent-sharing or productivity (Abowd et al., 1999; Card et al., 2018). Even job-level studies that enable within-occupation comparisons have not yet isolated the return to green tasks from the richer bundles of general skills that green jobs tend to require (Saussay et al., 2026; Vona et al., 2018). As a result, we do not know how much of the observed green wage premium workers can actually attribute to the green task content of their jobs, and therefore how strong the market incentive to acquire the skills required to perform these tasks really is.

We quantify the returns to green tasks using highly disaggregated online job vacancy (OJV) data for EU countries over the period 2018-2023. The richness of this data allows us to observe wage offers, detailed skill requirements and firm identity at the vacancy level. We develop a novel and transparent large language model (LLM)-based approach to identify green jobs from vacancy-level skills requirements. We then use this granularity to address the main potential sources of bias when estimating the green wage premium in order to provide a structural interpretation of it as the average return to green tasks.

First, hiring managers may manipulate the content of green vacancies to attract candidates with particular characteristics, for example by emphasising creativity, autonomy, cooperation, soft skills, or purpose. If workers value such non-monetary job attributes (Landini et al., 2025; Nikolova & Cnossen, 2020), wage differences between green and non-green jobs may not reflect green task content alone. We address this by constructing five groups of non-monetary job-attribute dummies from vacancy text and testing whether they account for the estimated green premium. Second, larger or more efficient firms may both pay higher wages and be more likely to post green vacancies. In that case, a green wage premium could simply reflect firm rents rather than returns to green tasks. We therefore estimate specifications with firm fixed effects (Abowd et al., 1999; Card et al., 2018; Song et al., 2019), comparing green and non-green vacancies within the same firm following Saussay et al. (2026). Third, prior evidence from the US shows that green jobs require a broader bundle of valuable skills in addition to green tasks (Saussay et al., 2026; Vona et al., 2018). To separate the return to green tasks from the return to general skill complexity, we control for broad skill families - IT, cognitive, management, social, and technical skills - and quantify their contribution directly in a classical Oaxaca-Blinder decomposition. This strategy to add a progressively stronger set of controls, therefore, allows us to isolate the average return to green tasks in a broad European setting marked by substantial institutional and industrial heterogeneity, and by a major policy push under the EU Green Deal.

Our empirical analysis yields the first decomposition of the green wage premium into firm rents, skill complexity, and a residual return to green tasks. We show that the overall green premium of 5.5%, estimated within 3-digit occupations - is a composite of three distinct components: firm-specific wage-setting accounts for roughly one half; the higher complexity of non-green skill bundles required by green jobs explains a further one tenth; and a residual return to green tasks of around 2% remains once both channels are absorbed. To put this in perspective, our residual return to green tasks is an order of magnitude smaller than recent estimates of the wage premium for AI skills, which Bone et al. (2025) estimate at around 23% using comparable vacancy data and a within-occupation specification. If the wage incentive for acquiring green skills is this much weaker than for other in-demand competencies, market forces alone may be insufficient to drive the skill reallocation required by the green transition, thus strengthening the case for active training and reskilling policies within broader green and climate policy packages.[1]

We contribute to the literature in four main ways. First, as a prerequisite to the wage analysis, we contribute to the measurement and identification of green jobs. Existing studies identify green work through green sectors (Antoni et al., 2015), green products (Becker & Shadbegian, 2009; Elliott & Lindley, 2017; Frattini et al., 2024), through firms classified as green (Godøy & Isaksen, 2025; Krueger et al., 2023),[2] or the green task intensity of occupations (Bluedorn et al., 2023; Vona et al., 2018).[3] While these approaches have generated important insights, they rely on aggregate proxies that may imprecisely capture the green content of very specific jobs, such as car repairer or roofers. We build on recent work that leverages OJV data to identify green jobs at the vacancy level (Curtis & Marinescu, 2023; Saussay et al., 2026), and develop a new transparent LLM-based method that identifies green jobs from vacancy-level skill requirements. We subject both the classification and the wage estimates to extensive cross validation and sensitivity analysis, e.g. varying the stringency of the green definition, and show that the main results are robust throughout.

Second, we contribute to the literature on the green wage premium. Existing estimates rely on three main approaches, measuring greeness at the sector-, product-, or firm-level, and generally find positive but mixed premia. Antoni et al. (2015) find a renewable-energy wage premium of 10% most of which reflects establishment and worker characteristics, Godøy and Isaksen (2025) estimate a green firm premium of 6.6% net of workforce composition, substantially smaller than the corresponding brown premium of 14.2%; and Frattini et al. (2024) find that expansions of green manufacturing production in the EU industries raise employment but not average wages. A limitation of these estimates is that they cannot distinguish the return to green tasks from other

[1]Popp et al. (2021) also provide supporting evidence, showing that the effect of the green part of the American Recovery and Reinvestment act is much larger in regions with a higher share of skills required in green jobs.

[2]Godøy and Isaksen (2025) classify establishments as green or brown using patent, R&D or export data, and then estimate an AKM model using matched employer-employee data for Norway. In this setup, the firm fixed effect net of workforce composition is interpreted as the green premium. Krueger et al. (2023) combines Environmental and Social Responsibility (ESG) ratings of the firm and sector-level measure of greenness to identify green firms in Swedish administrative data, and similarly interpret the firm effect as a green wage premium.

[3]Cross-occupation comparisons faces several limitations. For example, green and non-green tasks frequently coexist within the same occupation (Saussay et al., 2026; Vona et al., 2018) and there are well-known problems with crosswalks imputing O*NET green tasks to EU occupations (Vona, 2021).

firm- or sector-level attributes correlated with greenness. A second strand leverages cross-occupation differences in green task intensity. Estimates range from 4% in the US (Vona et al., 2019) to around 7% across a broader set of developed countries (Bluedorn et al., 2023) and in Japan (Kuai et al., 2025).[4] However, these comparisons operate at a coarse level of aggregation, conflating the return to green tasks with other occupation- and worker-level unobservables. A third, more recent strand uses OJV data to estimate the premium within occupations while more cleanly controlling for other occupational characteristics , reporting premia of between 3-4% for the UK (Bone et al., 2025) and 3-5% for the US (Saussay et al., 2026). We build on the last strand but go further: rather than estimating a single green wage premium, we decompose it into its underlying drivers and provide the first evidence on the relative importance of each component. In addition, we provide a structural interpretation of the residual component as average return to green task.

Third, we bring the literature on non-monetary job attributes into the analysis of green wages. A growing literature argues that workers value intrinsic aspects of jobs, such as meaningfulness, ethical alignment, and social impact, and may accept lower wages in exchange (Nikolova & Cnossen, 2020). In the sustainability context, survey and experimental evidence show that some workers are willing to forgo part of their wages to work in more sustainable or less ethically objectionable jobs (Burbano, 2016; Colonnelli et al., 2025; Hedblom et al., 2019; Schneider et al., 2024). This raises a direct identification concern: if green jobs bundle pro-social or purpose-oriented characteristics that workers value, firms could offer lower wages and still fill vacancies, biasing estimated green wage premia downward. This concern is supported by recent evidence that workers in greener occupations report higher perceived meaningfulness of their work (Landini et al., 2025). Indeed, Krueger et al. (2023) interpret wage penalties in more sustainable firms as consistent with a compensating differential for non-monetary attributes, although this interpretation rests on ESG-based measures of greenness whose credibility has been questioned. Our contribution is to test this channel directly, using vacancy text to construct explicit controls for non-monetary job attributes and assess whether they account for the estimated green premium.

Fourth, we provide broad European evidence on the green wage premium using vacancy data covering multiple EU countries. Most existing estimates for Europe are drawn from single-country settings: Germany (Antoni et al., 2015); Norway (Godøy & Isaksen, 2025); the Netherlands (Elliott et al., 2024); or Sweden (Krueger et al., 2023). This limits external validity given the cross-country heterogeneity in labour market institutions, industrial structure, and climate policy ambition across Europe. The few multi-country studies rely on crosswalks with O*NET (Bluedorn et al., 2023), which are subject to a lack of occupational granularity (Vona, 2021), or on ESCO green skill labels that adopt a broader definition of greenness than ours and still operate at the occupation rather than vacancy level (Zaussinger et al., 2025). Our multi-country setting also covers a period of

[4]Using more granular US occupational data, Popp et al. (2021) show that the green-fossil fuel pay gap varies by skill level, with green jobs paying more only in low-skilled occupations.

ambitious climate policy under the EU Green Deal, allowing us to study returns to green tasks in the context of a major policy push toward decarbonization.

The remainder of the paper is organized as follows. Section 2 presents the Lightcast data for Europe and the LLM methodology used to classify green vacancies. Section 3 provides descriptive evidence on the distribution and evolution of green jobs in Europe. Section 4 introduces the empirical strategy and presents the the main results on the green wage premium. Section 5 analyse the skill profile of green jobs and their role in explaining the green wage premium. Section 6 concludes.

2 Data and methodology

Our objective is to assess the monetary returns to green tasks across a broad range of green-related activities. A prerequisite of for our analysis is to define what green tasks and jobs are. As discussed in the introduction, existing approaches identify green work through firms, sectors, occupations, or tasks, each with different trade-offs between coverage and precision. We build on recent work using OJV data and skill-based approaches to identify green jobs at the vacancy level (Bone et al., 2025; Saussay et al., 2026), and propose a new method that exploits recent advances in LLMs.

2.1 Measuring green tasks with OJV data

Our primary data source is the Lightcast job vacancy database for Europe, a large and detailed dataset of online job vacancy postings scraped from thousands of websites. Each observation corresponds to a unique job opening and contains rich information on the vacancy. Lightcast extracts information as standardized variables with varying degrees of coverage, including the job title, 3-digit ISCO occupation, Lightcast specialised occupation, industry code (NACE), firm name, job location, educational requirements, skill requirements, wage offer, and whether the role is part-or full-time. The granularity of these data is central to our analysis, as it allow us to compare green and non-green jobs within the same occupation.

A key conceptual point is that our object of interest is the green wage premium, understood as the average return associated with performing green tasks (Autor & Handel, 2013; Deming, 2017; Vona et al., 2019). However, tasks are not directly observed in OJV data. Instead, Lightcast data report the skill requirements attached to each vacancy. More specifically, the way we observe the skill content of a particular position is not as unstructured text, but as a vector of skills. Lightcast extracts skill requirements from the raw advert texts, and identifies 33,419 unique skills across all ads, grouped in a hierarchical structure of skill categories and sub-categories. We also know if each skill belongs to one of the following broad fields: *common*, *specialised* or *certification*. In addition, any item appearing in these categories can be further tagged as *language* or *software* skills[5] Specialized skills and certifications, excluding language and software specific ones, account together for 68% of all skills (22,814).

We argue that, among these broad fields, specialised and certification skills provide a close proxy for the task content of jobs. Unlike common skills, these fields refer to job-specific competencies as well as specific tools, technologies and bodies of knowledge, and therefore capture what workers are expected to do on the job - that is: tasks. By identifying green jobs through the text of specialized and certification skills, our approach follows the task-based labour literature in treating observed job requirements as empirical manifestations of underlying tasks (Acemoglu & Autor, 2011; Autor & Handel, 2013). It is also in the spirit of recent work using Lightcast data in the AI context, which adopts a task-based perspective while operationalising it through detailed skill requirements observed in vacancies (Acemoglu et al., 2022). Throughout the paper, we therefore interpret specialised green skill requirements as footprints of green task content in vacancy data.

In addition to the granular information about skill requirements, Lightcast assigns each job a *specialized occupation* using the Lightcast Occupational Taxonomy (LOT).[6] Following the literature on new work as proxy for new tasks (Autor et al., 2024; Lin, 2011), we use occupational titles in the Lightcast taxonomy as another signal to identify a green job vacancy. This allows us to use more information to identify green job ads and potentially fully green occupations such as *Solar Installer* or *Wind Turbine Technician*.

2.2 Green tasks selection algorithm

Having established a good proxy of tasks in the Lightcast dataset, the next step is to develop a transparent and replicable method to identify the specialized skills and occupations that are related to green activities. To this end, we propose an LLM-based classification approach that assesses whether each specialized skills or occupations is specifically related to environmental activities as defined in EU Regulation 2021/2139. The classification proceeds in three automated stages followed by a manual review step, and is applied separately to *specialized skills* and *specialized occupations* (referred to jointly as "items" in the rest of this section).

The first step is a prompt asking whether the item is core and specific to climate change mitigation or adaptation, or to closely related non-climate environmental activities such as waste management or ecosystem management. Given the European setting of this paper we ground our

[5] Skills are competencies at specific tasks or familiarity with specific subjects and tools acquired through education or experience. *Common Skills* include *e.g. Accountability*, *Curiosity*, *Honesty*, *Supervision* or *Team Building*. Certifications skills include *e.g. Accredited Tax Advisor*, *GIAC Certified ISO-17799 Specialist* or *LEED Green Associate*. *Spoken Languages* and *Software* skills are self explanatory. 88% of skills (29,582) are *specialized skills* and include *e.g. Aluminium Wires*, *Ethanol Fuel*, *Nuclear Design*, *Photovoltaics* or *SEC Filing*.

[6] With 1,894 *specialized occupations*, LOT offers a highly granular occupational classification, which is also aggregated to 800+ *occupations*, 180+*occupation groups*, and 28 *career areas*. Examples of *specialized occupations* include Surgeon, Mortgage Underwriter, Refrigerated Truck Driver and Energy Efficiency Specialist.

classification of green activities in the EU Commission Delegated Regulation (EU) 2021/2139 (European Commission et al., 2021), which defines the "conditions under which an economic activity qualifies as contributing substantially to climate change mitigation or climate change adaptation" and "causes no significant harm to any of the other environmental objectives". Relative to broader labour-market taxonomies of green skills, this source text provides a narrower and more policy-relevant benchmark for identifying climate-related task content. This results in an average of 1,089 green skill candidates and 54 green occupation candidates per model[7].

Items that pass the initial binary screen enter a second prompt, which assigns each item to nine broad green categories: decarbonization of energy, transport, buildings, or industry; climate-CCS; climate adaptation; climate-general; waste management; or forestry-ecosystem management. Items that do not fit these categories are assigned to the *Not-climate-nor-green-related* group. This step catches items that are too broad or vague to be confidently attributed to green activities, such as e.g. *Sewage Collection And Disposal*, *Soil Management* or *Reverse Osmosis*.

The nine groups are used as a consistency check on the binary screen rather than as an additional outcome: a candidate green item must be assignable to a concrete environmental activity, not merely contain language that is loosely environmentally related. This is consistent with recent evidence that LLM-based classifications are more reliable when the label space is fixed and checked through multi-stage or hierarchy-aware prompts rather than through a single binary judgment (Buckmann & Hill, 2025; Ma et al., 2025; Xia et al., 2025; Zhu & Hardt, 2026).

In a third prompt, we apply a specificity screen to items that were assigned one of the nine green categories. This stage complements the residual category used in the previous step. The residual category in the second prompt excludes items that cannot be mapped to a green activity at all, whereas this third classification step flags items that can be mapped to such an activity but are too general to identify green task content in vacancies. For instance, *Water Treatment* or *Building Automation* can be associated with waste management or building energy use, but many postings using these terms need not involve climate- or environment-specific tasks. We therefore ask whether each item is *Too broad or too vague* or *Specific climate or green*.

Rather than relying on a single model, we run the three prompts across seven frontier models[8] and aggregate the outputs by ensemble vote. This limits the possibility of idiosyncratic model error in LLM text-classification performance, which is known to vary with model choice and prompt design (Schoenegger et al., 2024; Trust & Minghim, 2024; Yang et al., 2025). Following best practices in recent economics work that treats LLM classification as a measurement problem (Chatterji et al., 2025; Galiani et al., 2026; Juhász et al., 2025; Ludwig et al., 2025), we define the possible green

[7]Green skill candidates range from 367 to 2,364 across the 7 LLMs used in the classification exercise. Green occupation candidates range from 40 to 71.

[8]These are OpenAI gpt-oss-120b, Deepseek v3.2, Mistral Large 3 675B Instruct, Meta Llama 4 Maverick, Anthropic Claude Sonnet 4.5, OpenAI GPT 5.1, and Google Gemini 2.5 Pro.

labels to be used in the classification task *ex ante*, disclose the prompt structure (see Appendix B.2), and validate classifier outputs against both human review and external classifications of green skills (see below).

In the final step, we define a set of voting rules to aggregate item classification results across all 7 models. Let g_i denote the number of models that assign item i to one of the nine green categories following Prompt 2, and let b_i denote the number of those models that subsequently classify the candidate green item as *Too broad or too vague* following Prompt 3. We apply the following rules to elicit green skill candidates:

Table 1: Voting rules to aggregate skill classifications across LLMs

Rule	Description	Skill count
$g_i = 7$	When all seven LLMs agree that skill i should be classified as green, we include it directly as part of our set of green skills	207
$g_i \geq 4$ and $b_i \leq g_i/2$	If a majority of LLMs consider a skill green while less than half considered it too broad, we include it in our set by default	286
$g_i \geq 4$ and $b_i > g_i/2$	If instead a majority of LLMs consider a skill green but *at least half* of them also considered it too broad, we impose a manual verification step	97
$g_i = 3$	Conversely, we exclude skills classified as green by only three LLMs, but review them manually to guard against false negatives	124
$g_i \leq 2$	Skills considered green by fewer than two LLMs ($g_i \leq 2$) are excluded	22,100

The manual review follows pre-specified criteria. We retain a skill only if it is both assignable to one of the nine environmental categories and specific enough that its presence in a vacancy is informative about green task content. We reject skills that refer to generic technologies, broad environmental domains, conventional fossil-energy activities, or ordinary engineering and compliance tasks with substantial non-green uses. Including a potential false positive candidate ($g_i \geq 4$ and $b_i > g_i/2$) or false negative ($g_i = 3$) requires agreement by at least four of the five co-authors. We end up excluding 26 false positives and including 29 false negatives.

For specialised occupations we impose a stricter final rule, because an occupation-level match classifies all vacancies under that occupational title as green. We therefore retain only titles verifying $g_i \geq 6$ and $b_i = 0$, and only if at least four co-authors judge that jobs classified under the title would plausibly involve green task content. This manual validation leaves 17 fully green specialised occupations out of 20 titles satisfying the LLM rule.

This results in a final set of 591 green skills and 17 fully green specialised occupations (Appendix Tables D5 and D.6). We define a vacancy as green if it lists at least one of these green skills or belongs to one of the fully green specialised occupations. For later analyses, we define the low-carbon subset as all green types other than waste management and forestry-ecosystem management. In sum, this procedure translates a task-based concept of green work into a vacancy-based empirical measure built from specialised skill requirements and specialised occupations.

To assess the robustness of our results to these design choices, we construct broader and narrower variants of our own classification to test the sensitivity of the wage results. Specifically, the narrow set only includes skills classified as green by at least six LLMs without being considered too broad by a single one of them ($g_i \geq 6$ and $b_i = 0$), while the broad variant includes any skill considered green by at least three LLMs ($g_i \geq 3$). Green job shares under these alternative definitions are reported in Section 3.1 and Appendix D, and wage regression results in sections 4 and 5.

2.3 Details on the EU Lightcast dataset

The data used in this paper covers the period 2018 to 2023. In Section 3, we use a broad sample covering the EU27, together with Norway and Switzerland. After dropping a small portion of ads with missing occupation information, the broad sample contains roughly 180 million observations. From Section 4 onwards, we focus on wage and skill gaps between green and non-green jobs. Because missing wage information is a pervasive feature of OJV data, we restrict the analysis to the following 12 countries, where sample size remain large enough to ensure statistical power: France, Germany, Netherlands, Austria, Spain, Ireland, Czech Republic, Poland, Italy, Belgium, Portugal, and Denmark. While these countries account for about 90% of the broad sample, the sample used to estimate the green wage premium is much smaller because around 86% of ads in the full 29 country sample lack salary information, and 22.4% lack geographical information.[9]

The Lightcast dataset reports annual wages as well as information on whether the job offered is part- or full-time. After deflating the salary using the country-specific Consumers' Price Index and trimming outliers,[10] the final sample used for the wage and skill gap analyses contains 20.78 million observations. Appendix Table C.3 reports descriptive statistics for advertised salaries in this sample, overall and by occupation and sector.

As with all OJV data, the Lightcast database provides a rich and timely measure of employer demand, but it also has limitations. First, it captures the flow of labour demand rather than the stock of employment, so it is not directly comparable to worker- or occupation-based data and may over-represent growing firms or sectors. Second, the use of posted vacancies means that we observe firms' wage offers and stated skill requirements, but not the realised match or the actual equilibrium wage. Third, OJV data may under-represent vacancies that are filled through other channels, such as informal recruitment or internal promotions, which are well-known to be particularly important in Southern European countries (Pellizzari, 2010).

[9] See Table A.1 for missing value shares for the key variables.

[10] We define salary outliers as ads with salary below the 0.5^{th} or above the 99^{th} percentiles. We also drop ads with more than 50 skills.

Finally, previous work has shown that OJV data may not be representative of all occupations, sectors, or countries (Napierała et al., 2022; Vermeulen & Amaros, 2024). We assess the representativeness of the Lightcast data by comparing it to Labour Force Survey (LFS) data[11] in Appendix A. As expected, the Lightcast data over-represent some groups, for example, Germany, France and the Netherlands and high-skilled occupations. It also under-represents others, including Italy and Spain and some middle to low-skilled occupations where informality is more prevalent in sectors as construction, agriculture and cleaning. To limit these representativeness concerns, we always re-weight job vacancies using country specific 3-digit ISCO employment from the LFS, averaged over 2018-2023. More specifically, we compute the weighted green job share in country c as $\sum_k \frac{\bar{L}_{kc}}{\bar{L}_c} \frac{n_{gkc}}{n_{kc}}$, where $\bar{L}_{kc}$ is average employment in occupation k and country c, $\bar{L}_c$ is the average employment in country c, n_{gkc} is the number of green ads in occupation k and country c, and n_{kc} the total number of ads in occupation k and country c. In the regression analysis from Section 4 onwards, we use $\frac{\bar{L}_{kc}}{\bar{L}_c}$ as regression weights for job ads i in country c and occupation k.

3 Descriptive evidence on green jobs in Europe

To give context to our analysis, we present a descriptive analysis resulting from our new data. Importantly, this analysis provides the first full account of the distribution and evolution of green jobs in Europe, representing an important contribution of this paper.

Figure 1 shows the evolution of green job shares over 2018-2023. The aggregate green job share increases from 2.6% to 3.6% over the period, suggesting a gradual expansion of green employment. We observe a similar growing trend for the low-carbon subsample, as shown in Appendix Figure C.1, where the shares rise from 1.2% to 2.0% between 2018 and 2023. These levels are consistently above the U.S. estimates reported by Saussay et al. (2026), which remain broadly flat and below 1% between 2010 and 2019 using comparable job-level data. Green and low-carbon job shares therefore appear to be higher in Europe than in the United States, consistent with Europe's more ambitious climate policy agenda and stronger political commitment to the green transition. Our estimates also remain in the range of previous occupation-level studies using task-based approaches (Bluedorn et al., 2023; Vona et al., 2019).

The evolution of green employment is also heterogeneous across low-, middle- and high-skilled occupations.[12] Green job shares are highest among low-skilled occupations throughout the sample period, increasing from 4.3% to 5.3% between 2018 and 2023. High-skilled occupations also see a marked rise, from 2.1% to 3.4%, whereas middle-skilled occupations remain comparatively stable, at

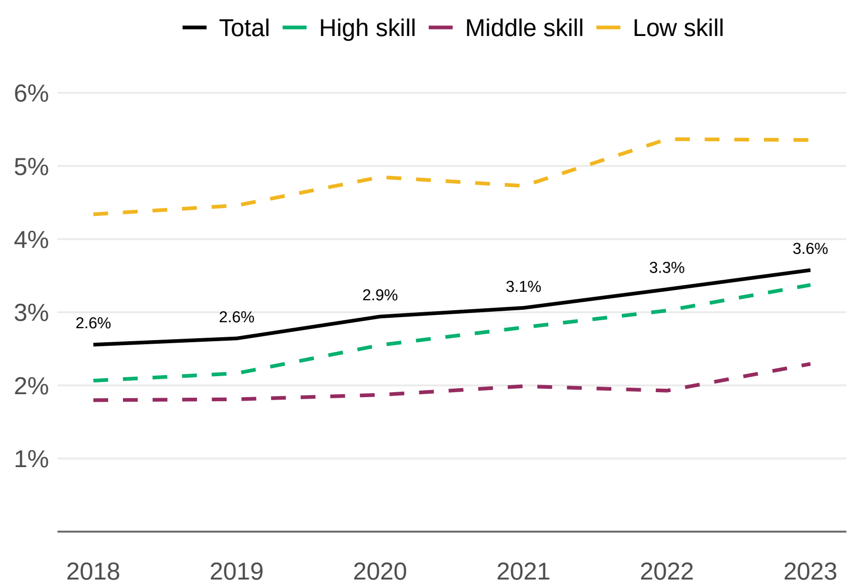
[11] EU and Swiss Labour Force Survey data are only available up to 2022. We therefore carry forward the last observed values to extend the comparison to 2023.

[12] These broad skill groups are classified based on the 1-digit ISCO occupation classification rather than the educational requirements specified in the ads. See Table C.1 for the correspondence between skill levels and occupations.

1.7% in 2018 and 2.3% in 2023. This ranking, with the highest shares among low-skilled occupations, is consistent with the U.S. evidence in Saussay et al. (2026) and questions the belief that the green transition, like the parallel digital transition, will be skilled-biased against manual workers (Consoli et al., 2016; Marin & Vona, 2019).

We present a more refined breakdown of green job shares by 1-digit ISCO occupation over 2018–2023 (Appendix Figure C.2), and on aggregate over the sample period by both 1-digit ISCO occupation (Appendix Table C.1) and 2-digit ISCO occupation (Appendix Table C.2). A key pattern is that, although green job shares are often highest in some low-skill occupations in levels, the fastest growth over the sample period occurs in high-skill occupations. Across all 1-digit high-skill groups, green job shares increase by roughly 1 and 1.6 percentage points during the sample period. Within this group, scientists & engineer professionals and associate professionals, and production managers have the highest green job shares, at above 6% and 4.7%, respectively (Appendix Table C.2).

Figure 1: Evolution of green job shares, 2018-2023

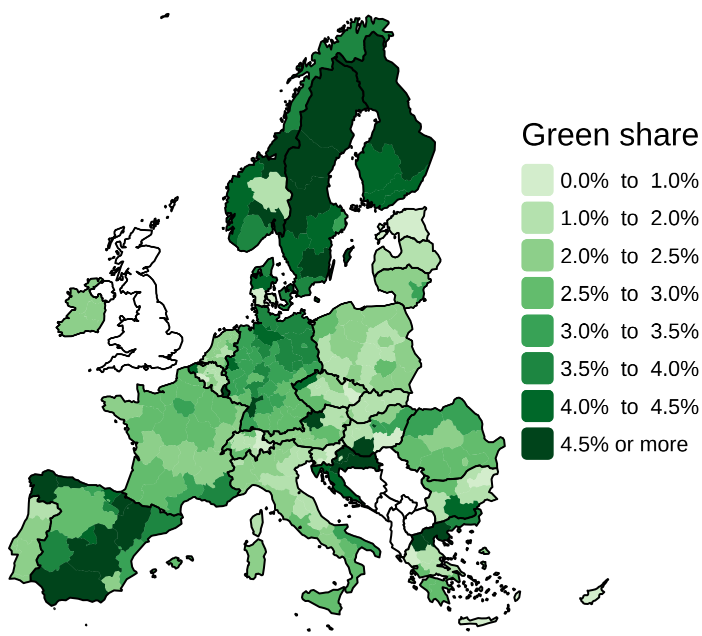


Notes. This figure includes EU27 countries plus Norway and Switzerland, and shows green job shares calculated using country-specific ISCO 3-digit occupation employment as weights. The annotations indicate aggregate green job shares (i.e. for all skill levels together). High skill covers ISCO 1-digit occupations 1, 2, and 3; middle skill covers occupations 4, 5, 6; low skill covers occupations 7, 8, 9.

Middle-skill categories display more heterogeneity: skilled agricultural, forestry, and fishery workers show very high green shares, but these remain relatively stable over time, whereas clerical and service workers record more modest green job shares. Among low-skill occupations, patterns also differ across groups. Plant and machine operators, which includes train and bus drivers, have relatively high but stable green job shares, rising from 4.2% in 2018 to 4.6% in 2023. By contrast, craft workers, which includes electronic trades workers such as solar panel installers, see a more marked increase from 3.1% to 4.6%. Elementary occupations, which includes refuse workers, also rise, from 7.8% to 8.6%. Within the low-skill group, the greenest 2-digit ISCO occupations are electronic trades workers (13.1% green job share), drivers and mobile plant operators (5.7% green), and refuse workers (35%).

Sectoral heterogeneity is also pronounced (Appendix Figure C.3). Utilities exhibit by far the highest with the weighted share rising from 19.8% in 2018 to over 25% in 2023. This pattern is consistent with the fast growth of renewable-energy generation in several EU countries. Green job shares also increase in construction, services and manufacturing, though from much lower initial levels.[13] In the primary sector, mining records a marked increase in green job share, driven largely by a handful of high-skill occupations, including chief executives, production managers, scientists and engineers, and business and administration professionals, whereas agriculture shows a slight decline over the sample period.[14] Taken together, these varying patterns across occupations and sectors highlight a high degree of heterogeneity in the development of Europe's green economy.

Figure 2: Green job share by NUTS2 region, 2018-2023



Notes: This map depicts the country-level 3-digit ISCO employment weighted share of ads that are green for NUTS2 regions. Countries not in the sample are shown in white.

Focusing on a spatial dimension, we find considerable regional variation in the prevalence of green employment opportunities across Europe (Figure 2 and Appendix Figure C.6). Green job shares across NUTS2 regions over 2018 to 2023 span from 0 to above 5%. Regions with the highest shares are focused around Northern Europe, particularly in Scandinavia and Germany, but also Spain and Hungary. This broad concentration of green activity is consistent with the regional

[13] Low carbon job shares by sector, shown in Appendix Figure C.4, display qualitatively similar patterns.

[14] Appendix Figure C.5 shows the green and low-carbon shares for primary sectors. Note that primary sectors comprise of only 0.4% of the total sample in 2018-2023 and 1.2% of the subsample with non-missing NACE sector.

distribution of green industrial production documented by Frattini et al. (2025). By contrast, lower shares are more common in parts of Eastern and Southern Europe.[15]

The observed clustering likely reflects broader differences in regional development. Regions with higher green job shares also tend to be those with stronger economic capacity, higher level of human capital (e.g., STEM and tertiary-educated workers), and greater ability to finance and implement green investments. In other words, the spatial distribution of green postings appears more consistent with variation in industrial structure, skills, and policy capacity than with natural resource endowments (e.g., solar or wind potential) alone.

3.1 Validation of the green job classification

We validate our LLM-based classification by comparing the implied green job shares both at the country- and 3-digit occupation-level, with two external benchmarks: the ESCO green skill label (ESCO Publications, 2022)[16] and Lightcast's experimental green skill classification.[17] Relative to Regulation 2021/2139, the ESCO definition of green skills is broader in some respects, while Lightcast's is closest to ours in scope. We also compare it with the broad and narrow variation of our own definition introduced in Section 2.2. Appendix D provides details of the comparison.

The three classifications produce different levels of green employment: our employment-weighted green job share across the 29-country sample is 3.3%, compared with 13.2% under ESCO and 2.3% under Lightcast. Other studies using ESCO find relatively higher shares of green employment (Maldonado et al., 2024), and ESCO's own report highlights the problem of false positives in their classification (ESCO Publications, 2022). Average shares are 1.6% and 3.7% using the narrow and broad definitions, respectively, of our own green classification (Appendix Figures D.1 and D.2). Despite these differences in levels, the cross-sectional patterns are highly correlated. Country-level and occupation-level green job shares are closely aligned across all three definitions, particularly between our classification and Lightcast's (Appendix Figures D.3 and D.4, Tables D.2 and D.3). The evolution of green employment over time also tracks consistently across taxonomies, with all three showing a gradual increase between 2018 and 2023 (Appendix Figures D.5 and D.6). This is further confirmed when considering our narrow and broad sets of green skills. The agreement across

[15]These spatial patterns are broadly similar for low-carbon job shares (see Appendix Figure C.7), though overall shares tend to be lower.

[16]European multilingual classification of Skills/Competences, Qualifications and Occupations (ESCO) is the European counterpart of the US occupational information network O*NET. Developed by the European Commission, ESCO classifies approximately 3,000 occupations and nearly 14,000 skills and competences across 28 languages, mapping the relationships between them using the International Standard Classification of Occupations (ISCO). Their list of 571 green skills is based on the suggested definition by the European Centre for the Development of Vocational Training (Cedefop). Cedefop (2012) states that green skills are "the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment".

[17]This classification is done manually using as inputs ESCO, O*NET and the Lightcast's own taxonomy (i.e. Technologies (2019)), the latter definition is used by Bone et al. (2025).

independently constructed classifications - differing in methodology, scope, and source text - suggests that our approach captures meaningful variation in the green content of jobs while minimising the risk of false positive present in the ESCO classification.

4 Green wage premium

This section presents the core econometric choices and results of the paper. We first introduce the empirical framework used to estimate the green wage premium. Afterwards, we present the baseline results and two critical extensions that allows to enhance the credibility of our empirical framework.

4.1 Empirical strategy

Inspired by the task-based framework and following the related job-level approach in Saussay et al. (2026), we estimate the green wage premium using standard Mincerian wage regressions at the job ad level. Our baseline specification is:

$$log(w_{itor(c)}) = \delta^g Green_{itor(c)} + \rho_{r(c)} + \gamma_{ct} + \eta_o + \varepsilon_{itor(c)}, \tag{1}$$

where $log(w_{itor(c)})$ is the log annual salary posted in job ad i in year t, NUTS-2 region r in country c, and occupation o (measured at the 3-digit ISCO level). $Green_{itor(c)}$ is a dummy variable equal to one if the job is classified as green. In an extension, we replace this dummy with $Low\,Carbon_{itor(c)}$, which identifies the subset of green tasks that directly contribute to decarbonization. The coefficient of interest, δ^g captures the wage premium associated with green jobs. More precisely, and consistent with the task approach, it is useful to interpret the green wage premium as the average return associated with performing specific tasks - green in this case - relative to otherwise comparable jobs (Autor & Handel, 2013; Deming, 2017; Vona et al., 2019).

The specification of equation 1 includes a set of controls designed to absorb the major confounding factors that may contaminate the estimation of δ^g. Region fixed effects $\rho_{r(c)}$ account for time-invariant wage differences across regions associated, for instance, with agglomeration effects; country-by-year fixed effects (γ_{ct}) allow wages to respond flexibly to country-specific macroeconomic conditions; and 3-digit ISCO fixed dummies (η_o) control for the broad set of occupational skills and exposure to other structural transformations and enable within occupation comparisons. $\varepsilon_{itor(c)}$ is the stochastic error term. δ^g is therefore identified by comparing a green and a non-green job ad posted in the same country-year, region and occupation. Standard errors are clustered at the 2-digit ISCO-by-NUTS2 level. As in the descriptive analysis, we weight observations using country-specific ISCO 3-digit employment levels from the EU-LFS to improve representativeness; unweighted estimates are reported in Appendix E.1.

This baseline strategy addresses major sources of compositional bias, but it does not justify a causal interpretation of δ^g as the return to green tasks. Even conditional on the set of controls included in equation 1, The choice of posting a green job is likely to be correlated with unobservable firms' characteristics as well as with the profiles of expected applicants. In the returns to task literature, the first and main concern is endogenous sorting of workers with different, often unobserved, skills into jobs with different task content (Autor & Handel, 2013; De La Rica et al., 2020; Gathmann & Schönberg, 2010; Hurst et al., 2024).[18] In our setting, this concern does not apply because we observe posted wage offers rather than realized post-match equilibrium wages.

However, there are four remaining sources of potential bias that may contaminate the average returns to green tasks in OJV data. The rich set of job characteristics that can be extracted from a job vacancy allows us to mitigate these biases.

First and related to sorting, managers can use wage offers strategically as signals to discriminate between green and non-green potential applicants, based on their expected characteristics. In line with the theory of compensated wage differentials (Rosen, 1986), wage offers may therefore reflect not only the value of green task content itself, but also discount the value of expected worker attributes associated with green vacancies. More specifically, green positions may offer non-monetary attributes including ethical or purpose-oriented content, that make them attractive to some workers with environmentally-friendly attitudes, even at lower pay which would bias downward the estimated returns to green tasks. To control for job attributes that are correlated with the non-monetary benefits or the ethical orientation of the potential applicants, we refine our empirical strategy by including a set of five dummies that proxy intrinsic nonmonetary benefits of a vacancy, such as ethical and meaningful work. In doing so, we reassess the returns to green tasks narrowing the comparison to jobs that, as green ones, have positive nonmonetary or ethical attributes (see Section 4.3 for details).

Second, a further concern is that the estimated premium may reflect firm-level wage setting rather than task content. If firms that pay higher wages for reasons unrelated to green tasks (e.g. larger, more efficient) are also more likely to post green jobs, specification 1 will conflate the expected marginal productivity of workers in green task with firm rents. Following the literature on firm-specific wage premia (Abowd et al., 1999; Card et al., 2018; Song et al., 2019), we therefore estimate a preferred specification that adds firm fixed effects:[19]

$$log(w_{itojr(c)}) = \delta^g Green_{itojr(c)} + \rho_{r(c)} + \gamma_{ct} + \eta_o + \boldsymbol{X}_i \boldsymbol{\gamma}^\top + \mu_j + \varepsilon_{itojr(c)}, \tag{2}$$

where j indexes the firm, $\boldsymbol{X}_i$ includes a vector of job ad characteristics such as general skills and

[18] For instance, if complex tasks are more likely to be taken by talented workers, returns to there tasks may just reflect returns to better skills of these workers.

[19] Typically, firm fixed effects account for differences in rent-sharing, firm's job ad strategy and an efficiency wage premium (Burdett & Mortensen, 1998; Card et al., 2018).

ethical attributes, and μ_j are firm fixed effects. This specification is more compelling - it identifies the green wage premium by comparing green and a non-green vacancies posted by the same firm, in the same 3-digit occupation, and in the same country-year and region. Under the assumption that, conditional on these controls, such job offers differ only in their green task content, $\hat{\delta}^g$ can be interpreted as the average return to green task. Importantly, this specification does not only allow to isolate the returns to green tasks, but can be also used to decompose the extent to which firm rents explain the green wage premium.

A third issue is measurement error in classifying green jobs. If our binary indicator does not perfectly capture green task content, the estimated premium may be biased. Under classical measurement error, the bias is likely to be attenuating, so the baseline estimates would be conservative. However, misclassification may also be non-classical if, for example, some jobs contain richer green task content than others within the same category. To assess the sensitivity of our results to this concern, we complement the baseline definition with robustness checks using both stricter and broader definitions of green jobs.

Lastly, as shown in previous research (Saussay et al., 2026; Vona et al., 2018), green position may require a broader and more complex set of valuable skills compared to similar jobs, which would bias upward the estimated premium if those skills are omitted. The role of skill composition is examined separately in Section 5, where we analyse the skill profile of green jobs and assess how far differences in observable skill bundles account for the estimated premium. Using an Oaxaca-Blinder decomposition, we test our expectation that higher occurrence of these general skills in green job ads account for a non-negligible fraction of the green wage premium.

The presentation of the results is organized as follows. In section 4.2, we present the baseline green premium retrieved from equation 1, together with some heterogeneity analyses along the sectoral, occupational and time dimension. In section 4.3, we first show the results for a specification augmented with the five dummies capturing nonmonetary job attributes. We then move to the specification of equation 2 with firm fixed effects, where the estimation sample is smaller due to the large fraction of ads without firm information (about 29% - see Table A.1 for the share of missing observations for each of the key variables). Finally, given the policy relevance of the topic, we assess in a separate section 5 both the skill profile of green jobs and the extent to which such jobs pay higher premia in skills that are known to have high market value (technical, cognitive, IT, managerial and social). This extension also allows us to account for drivers of the green wage premium associated with the skill content of the vacancy.

4.2 Main results

Table 2 presents the baseline results of the green wage premium, where the dependent variable is the posted annual gross salary in euros, deflated using the country-specific consumer price index.

In a parsimonious specification with country-by-year fixed effects only, green jobs pay 7.5% more on average than non-green jobs (column 1). Adding NUTS2 fixed effects leaves this estimate essentially unchanged (column 2), indicating that regional wage differences are not a major source of bias. Our preferred baseline specification additionally includes 3-digit ISCO occupation dummies and yields a green wage premium of 5.5% (column 3). This reduction suggests that green jobs are somewhat concentrated in occupational groups that already pay higher wages, but that a sizeable premium remains even within narrowly defined occupations. The low-carbon wage premium at 6.7% is larger than the broader green premium (Appendix Table E.1).

Our baseline estimate suggests the green wage premium is in the ballpark of previous estimates. Among recent vacancy-level estimates in the literature, Saussay et al. (2026) estimate a 6.5% premium for low-carbon vacancies in the U.S., falling to 3.7% once firm fixed effects are included, while Bone et al. (2025) find a smaller premium of around 3% in UK vacancy data without firm controls. At the occupation level, Bluedorn et al. (2023) report an average premium of about 7% across 31 countries over 2005-2019 relative to pollution-intensive jobs, Vona et al. (2019) find a 4% average premium in the United States over 2006-2014, and Kuai et al. (2025) estimate a green wage premium of 7.3% in the Japanese context.

Table 2: Baseline green wage premium

	(1)	(2)	(3)
Green job	0.075***	0.077***	0.055***
	(0.005)	(0.005)	(0.004)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our results are qualitatively robust to a range of robustness tests presented in Appendix E. First, unweighted estimates yield a smaller green premium of 4.0% (Table E.2). Second, excluding one country at a time shows that the result is not driven by a single country (Figure E.1). Third, the statistical significance of $\hat{\delta}^g$ is robust to alternative clustering of standard errors at either the NUTS 2 or ISCO-2 level (Tables E.3 and E.4). Fourth, replacing occupation fixed effects with

3-digit ISCO-by-year fixed effects that allow for flexible occupation-specific earning trends leaves the estimate unchanged (Table E.5). Fifth, the result is also robust in the smaller sample for which NACE 2-digit sector information is available (Table E.6).

Next, we explore heterogeneity along three dimensions: time, sector and occupation. In all the three cases, we augment the baseline specification of equation 1 by including an interaction between the green dummy and a set of indicator variables capturing the dimension of heterogeneity of interest (year, 1-digit NACE sectors, 1-digit ISCO occupations). Appendix Table E.7 shows that the average return to green tasks remains positive and statistically significant in every year. Although the estimates display some fluctuation, notably rising in 2019 and a dropping in 2021, there is no clear time trend, and we therefore remain cautious in assigning a strong economic interpretation.

In contrast, heterogeneity across sectors is substantial (Appendix Table E.8). Green premia are positive and statistically significant in all sectors except the primary one, but vary substantially in size. They are below the average in manufacturing (3.8%) and construction (4.6%), and well above it in services (8.5%) and utilities (11.5%).[20] The large premia in utilities, construction and, to a less extent, manufacturing are consistent with the fact that these sectors were the main beneficiaries of green subsidies within the EU Green Deal, suggesting that at least partial pass-through of subsidies to workers.

The relatively larger green premia in the service sector is less easy to interpret, because this sector is neither emission-intensive nor a major producer of green technologies, and contains a relatively small share of green jobs. One possible explanation is that some green tasks prevalent in services are especially valuable. Appendix Table E.9 show that returns to green tasks are particularly high among service and sales workers, just above 10%, despite a green job share below 2% for this occupational group. Appendix Table E.10 suggests that this result is driven by especially high premia among sales workers, who may be able to extract the rents generated by subsidies to new green products such as PV panels and EVs.

At the occupation-level, green wage premia also tend to be higher in high- and medium-skilled occupations than in low-skilled ones, with the exceptions of managers and skilled agricultural workers. Overall, the green transition seems to amplify existing trends in wage inequality associated with other structural transformations, such as automation and globalization. However, a notable difference with other structural transformations is that green premia are also positive for some low- and middle-skilled occupations.

[20] About 72% of ads are missing sectoral information. See Table A.1 for the shares missing for the key variables. Because the estimates at the sector level are done for a smaller sample, the average effect for this sample is 7.9% in our favourite specification, see Appendix Table E.6.

4.3 Firm rents and non-monetary job attributes

Section 4.1 identified the main threats to interpreting the baseline estimates as returns to green tasks: non-monetary job attributes and unobservable firm characteristics. We now assess the importance of these channels directly.

To capture non-monetary job attributes, we construct five groups of "skills" or job attributes that may make jobs attractive independently of wages: cooperation with colleagues (e.g., teamwork), independence at work (e.g., time management), soft skills (e.g., enthusiasm), explicit demand for creative tasks (e.g., intellectual curiosity); and purpose oriented or ethical content (e.g., strong work ethic or intercultural competence).[21] We then include five dummies in equation 1, each capturing the presence of at least one attribute for the specific group.

Table 3 shows that controlling for these non-monetary attributes has only a small effect on the estimated green premium. Comparing columns (1) and (2), the coefficient falls only from 5.9% to 5.5%. This suggests that managers are unlikely to lower wage offers in green jobs to extract non-monetary quasi-rents from potential applicants.

Even more important for the credibility of our identification strategy is the inclusion of firm fixed effects. Following Saussay et al. (2026), we add firm fixed effects to compare green and non-green vacancies posted by the same firm within the same occupation. Because firm names are missing for 28.7% of the estimation sample (see Appendix Table A.1), the regressions in Table 3 are estimated on a smaller sample. For comparability, column (1) reproduces the baseline estimate of equation 1 for this restricted sample. The resulting green premium of 5.9% is close to the 5.5% reported in Table 2, indicating that sample selection on firm identifiers is not driving the baseline result.

Once firm fixed effects are introduced, however, the estimated premium falls by nearly one half, from 5.9% to 3.0% (column 3). This indicates that firm rents account for a substantial share of the observed green wage premium. Column 4 which adds non-monetary job attributes on top of firm fixed effects, again yields only marginal further change, to 2.9%. These results are robust to clustering standard errors at the firm-level, which allows for unconstrained within-firm correlations in residuals (Appendix Table E.11), excluding large firms in top percentile of the job posting distribution that include also human resource providers (Appendix Table E.12), and limiting the analysis to low-carbon jobs (Table E.13). Importantly, the results are also qualitatively robust to both stricter and broader definitions of green skills (Tables E.14 and E.15). Table 3 therefore strengthens the credibility of our empirical strategy. The evidence suggests that non-monetary job attributes play only a limited role in explaining the green wage premium. In contrast, firm-specific wage-setting accounts for a substantial fraction of it, thus overstating previous estimates of the average return to green tasks (Bone et al., 2025; Kuai et al., 2025; Vona et al., 2019).

[21] See Appendix Table F.1 for the complete list of tasks for each group. In the next section we will present further analysis of the skill profiles of green workers with respect to these attributes.

Table 3: Green wage premium estimates, non-monetary job ad attributes and firm fixed effects

	(1)	(2)	(3)	(4)
Green job	0.059***	0.055***	0.030***	0.029***
	(0.004)	(0.004)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Non-monetary skills FE	No	Yes	No	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224
R^2	0.28	0.28	0.56	0.56

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Column (2) additionally controls for non-monetary job attributes. Column (3) introduces firm fixed effects, restricting the sample to firms posting multiple vacancies. Column (4) combines firm fixed effects and non-monetary job attribute fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221,942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Role of workers' general skills

This section extends the analysis by assessing the role of skill composition in the green wage premium. Previous work has shown that, although green jobs are not concentrated in high-skilled occupations, they tend to require more general skills than otherwise similar jobs within the same occupation (Saussay et al., 2026), especially technical and engineering skills (Popp et al., 2024; Vona et al., 2018). Together with firm rents, this richer skill content is therefore a natural candidate explanation for the premium documented in Section 4. We begin by revisiting the skill profile of green jobs in our data. We then extend the baseline specifications in equations 1 and 2 to estimate the returns to broad skill families in green jobs and to assess how far differences in observable skill bundles account for the green wage premium.

5.1 Skill profiles of green jobs

We exploit the rich skill information in the Lightcast data to compare the skill profiles of green versus non-green jobs. We proceed in three steps. First, we document unconditional differences in skill requirements. Second, following Saussay et al. (2026), we decompose these gaps into within- and between-occupation components. Third, we estimate conditional skill gaps using the same sequence of controls as in the wage regressions. Throughout this sub-section, we use the same subsample of job ads as in the wage regression analysis for comparability.

To assess skill profiles, we focus on five broad skill families: cognitive, IT, management, social, and technical skills.[22] These groups account for the main general skills that are rewarded in labour markets (see e.g. Altonji et al., 2012; Deming, 2017; Lindqvist & Vestman, 2011). In addition, we consider the five families of non-monetary job attributes described above.

Table 4 reports the share of ads within each job category (green and non-green) requiring exactly one skills from each family (extensive margin) and two or more skills (intensive margin). The main result in both panels is that green jobs are, on average, more likely to require skills from each of our ten skill families we study. This unconditional gap is particularly pronounced for technical skills on the extensive margin, 12.6% of green jobs require at least one technical skill, compared with 7.1% of non-green jobs. Gaps are smaller for the other four skill families (panel a), not present for soft skills and, at the intensive margin, for purpose-oriented attributes (panel B). Appendix Table F.3 highlights substantial heterogeneity across occupations. While skill gaps appear more pronounced in high-skilled occupations, the largest gaps in favour of green jobs are among "service and sales" especially for cognitive skills (14.1% vs. 4.7%) and technical skills (13% vs. 4.3%). These large skill gaps align with the large green wage premia documented earlier for service and sales jobs.

Table 4: Share of green and non-green job ads requiring skills from broad skill families and non-monetary job attribute categories (unconditional skill gaps)

(a) Broad skill families

	IT		Cognitive		Management		Social		Technical	
	1	2+	1	2+	1	2+	1	2+	1	2+
Not Green	4.9%	0.4%	16.2%	9.0%	18.8%	6.7%	13.1%	2.5%	7.1%	1.5%
Green	8.5%	1.0%	18.9%	13.4%	21.9%	9.8%	14.9%	3.6%	12.6%	3.5%

(b) Non-monetary job characteristics

	Cooperation		Creativity		Independence		Purpose		Soft skills	
	1	2+	1	2+	1	2+	1	2+	1	2+
Not Green	4.5%	0.1%	4.7%	0.2%	2.7%	0.1%	1.2%	0.0%	5.9%	0.6%
Green	5.5%	0.2%	7.4%	0.4%	3.8%	0.2%	1.6%	0.0%	5.7%	0.6%

Notes: Values indicate the share of ads for a given category (got green or green) containing exactly one or two-plus skills pertaining to the broad skill family or non-monetary job characteristic in the column header. Percentages refer to unweighted shares of ads. Calculated from the sample used in wage regressions and including all occupations.

In line with the task-based labour literature (Autor & Handel, 2013; Spitz-Oener, 2006), these green skill gaps arise mainly within narrowly defined occupations rather than across them. To show this, we decompose the total gap between green and non-green jobs into a within-occupation

[22]See Table F.2 in the Appendix for lists of the top 20 skills belonging to each family.

component and a between-occupation component at 3-digit ISCO level (details are provided in Appendix F.2). Appendix Table F.4 and Figure F.1 show that the within-occupation component is positive and always accounts for the large majority of the total gap for all the five broad skill families. In turn, the between-occupation component can be more positive or negative depending on the skill family. For instance, green occupations would display negative gaps in social and managerial skills if only across-occupation comparisons were possible; that is, if the data were aggregated at the occupation-level as in Vona et al., 2018. This result further supports our within-occupation, job-based approach to studying green skill and wage gaps. Notably, the within-occupation component is much larger than in the related U.S. evidence reported by Saussay et al. (2026).

These unconditional differences may, however, still reflect compositional effects. Green jobs may be disproportionately concentrated in high-skill occupations, locations, or firms, for example. To assess the robustness of the skill gaps, we therefore replicate the logic of wage regressions in Table 3 using skill requirements as outcomes. For each of the ten skill families, we estimate job-level regressions in which the explanatory variable of interest is a dummy indicating whether the vacancy is green, and the outcome is a dummy equal to one if the vacancy requires at least one skill from the family. In other words, we estimate extensive-margin skill gaps conditional on a set of covariates.[23]

Table 5 Panel A shows the main estimates for the extensive margin skill gaps in the five general skill families. In column 1, controlling only for country-by-year and NUTS2 fixed effects, the estimated gap is positive and statistically significant for all families. The magnitudes are economically sizeable, particularly for technical, management, and IT skills, where green jobs are 6 to 7.6 percentage point more likely than non-green jobs to require at least one such skills. Column 2 adds 3-digit ISCO occupation fixed effects, and column 3 further adds firm fixed effects. Even in the strictest specification, the extensive margin gap remains positive and statistically significant for all five families, although smaller in magnitude. For most families, green jobs within the same firm and occupation are still about 2-3 percentage point more likely to require these skills; for management skills, the gap remains as large as 6 percentage points.[24]

Panel B applies the same framework the five families of non-monetary job attributes, on both the extensive and intensive margins. The estimates suggest that even after controlling for firm heterogeneity, green jobs retain a small, positive extensive margin gap in cooperation, creativity, and soft skills (Table 5). Green jobs are 2.2 percentage points more likely to require a creativity-related attribute than non-green jobs, while the corresponding gaps for cooperation and soft skills are statistically significant but below 1 percentage point. By contrast, we find no meaningful gap

[23] Regressions are estimated using an OLS estimator. However, a probit model delivers similar results, which remains available upon request by the authors. In line with the wage analysis, we weight regressions using country-specific 3-digit ISCO employment (average over 2018-2023) and we cluster standard errors clustered at the 2-digit ISCO-by-NUTS2 region level.

[24] In the Appendix, we show that unweighted estimates deliver similar results (Table F.5. Low-carbon ads also display similar patterns (Table F.6).

Table 5: Conditional green skill gap: extensive margin estimates

	(1)	(2)	(3)
Panel A: Broad skills			
Green job - Cognitive	0.038***	0.035***	0.021***
	(0.004)	(0.004)	(0.002)
Green job - IT	0.076***	0.052***	0.030***
	(0.005)	(0.004)	(0.003)
Green job - Management	0.071***	0.077***	0.059***
	(0.006)	(0.004)	(0.004)
Green job - Social	0.029***	0.031***	0.016***
	(0.003)	(0.002)	(0.002)
Green job - Technical	0.063***	0.044***	0.033***
	(0.003)	(0.003)	(0.002)
Panel B: Non-monetary job attributes			
Green job - Cooperation	0.005***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
Green job - Creativity	0.039***	0.039***	0.022***
	(0.004)	(0.004)	(0.002)
Green job - Independence	0.004***	0.004***	0.000
	(0.001)	(0.001)	(0.001)
Green job - Purpose	-0.002***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)
Green job - Soft skills	-0.002	0.005***	0.008***
	(0.002)	(0.002)	(0.001)
Country $\times$ Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes
ISCO (3-digits) FE	No	Yes	Yes
Part-time FE	Yes	Yes	Yes
Firm FE	No	No	Yes
Observations	15,742,224	15,742,224	15,742,224
R^2	0.02	0.04	0.17

Notes: This table presents coefficient estimates from a series of job-level regressions. The dependent variable in each regression is a dummy variable indicating that a job requires at least one skill from the specified broad skill family or non-monetary job attribute category, and the explanatory variable is a dummy variable indicating the job is green. All regressions are estimated using the OLS estimator. Standard errors are clustered by ISCO 2-digit occupation by NUTS 2 region. Estimates are weighted by LFS ISCO 3-digit employment levels (avg. 2018-2023). Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

for independence or purpose-oriented attributes. Overall, the results suggest that green jobs offer some non-monetary content, particularly related to creativity, but that these differences are limited in both magnitude and scope. This helps explain why non-monetary job attributes had little effect on estimated green wage premium in Section 4.3.

5.2 Returns to skills in green jobs

Having shown that green jobs require broader bundles of valuable skills, we now return to the question: how far do these skill bundles explain the green wage premium? Because cognitive, IT, managerial, social and technical skills are generally rewarded in labour markets (Altonji et al., 2012; Deming, 2017; Lindqvist & Vestman, 2011), part of the premium associated with green jobs may simply reflect their higher prevalence in green vacancies. Omitting the presence of these skills may bias the estimated returns to green tasks upwards, if it also absorb the returns to general skills. To assess the importance of this channel, we augment the main specification with five dummies indicating the presence of at least one general skill from each broad family in the vacancy.

Table 6 shows that controlling for general skill dummies reduces the estimated green wage premium. Here, columns 3 and 6 are the new specifications; the others reproduce earlier results as benchmarks. Without firm fixed effects (columns 1-3), the coefficient falls from 5.9% to 4.1%, implying that differences in observable skill composition account for around 30% of the premium. With firm fixed effects (columns 4-6), it falls from 3.0% to 2.2%, implying that skill composition explains around 26% of the within-firm green premium.[25]

Table 6: Green wage premium estimates, controlling for broad skill families, non-monetary job attributes, and firm fixed effects

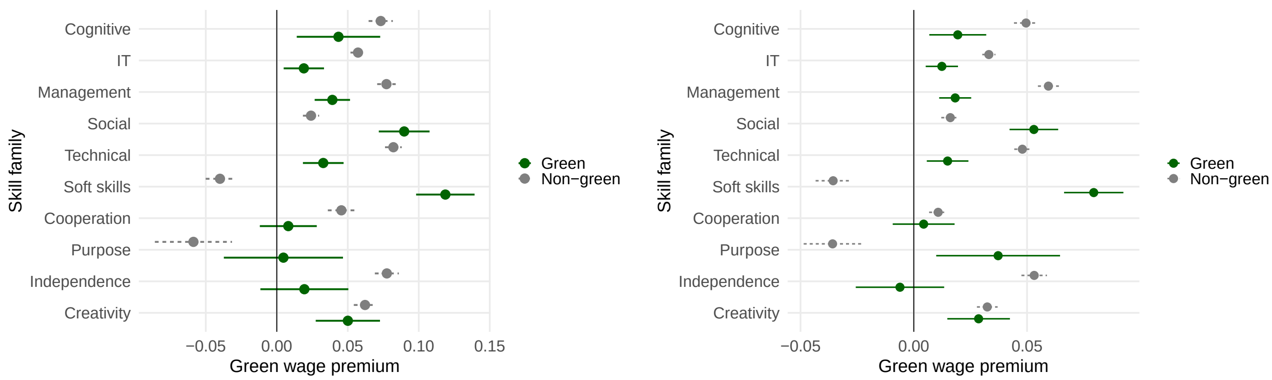
	(1)	(2)	(3)	(4)	(5)	(6)
Green job	0.059***	0.055***	0.041***	0.030***	0.029***	0.022***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Non-monetary skills FE	No	Yes	Yes	No	Yes	Yes
Broad skills FE	No	No	Yes	No	No	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224	15,742,224	15,742,224
R^2	0.28	0.28	0.30	0.56	0.56	0.57

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Columns (2) and (3) add non-monetary job attributes fixed effects, while column (3) further introduces broad skill-type fixed effects. Columns (4)–(6) include firm fixed effects. Column (5) adds non-monetary job attribute fixed effects, and column (6) additionally controls for broad skill-type fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[25] Roughly the same proportions apply to low-carbon jobs, see Appendix Table E.16. Results are also very robust to the use of a broader (Table E.18) or more stringent definition of green job (Table E.17).

We next ask whether the relevant general skills are simply more prevalent in green jobs, or whether they also earn different returns in green and non-green vacancies. To do so we augment the main specifications with interaction terms between the green job dummy and each skill family dummy, included one at a time. Figure 3 panel (a) reports the corresponding coefficients, and Appendix Table E.19 provides the point estimates.

Figure 3: Returns to broad skill families and non-monetary job attributes in green and non-green job ads



(a) base (b) with firm fixed effects

Notes: The figure reports estimated returns to skill requirements in green and non-green job postings at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Each point corresponds to the estimated coefficient on the indicated skill category, estimated separately for green and non-green jobs. Panel (a) reports baseline estimates including country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Panel (b) additionally includes firm fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Horizontal bars denote 95% confidence intervals based on standard errors clustered at the NUTS2–ISCO2 level. The vertical line indicates zero. Number of unique firms: 221942.

The bottom line is that returns to general skills and non-monetary job attributes tend to be positive, but not especially higher in green jobs. For the five general skills, the interaction terms are typically negative and statistically significant conjuring lower skill premia in green jobs (see also Appendix Table E.19). This indicates that these skills are rewarded less strongly in green vacancies, despite being more prevalent there. Social skills are the exception, being rewarded significantly more in green roles, possibly capturing the returns to green advocacy or marketing. For non-monetary job attributes there is no clear pattern. independence and cooperation pay only in non-green jobs, while ethical and purpose-oriented attributes have negative returns only in non-green jobs. Soft skills offers a positive premium in green jobs, but a negative one in non-green jobs.[26]

Adding firm fixed effects in Figure 3 panel (b) (see also Table E.19) confirms the same broad pattern, while also showing that firm rents account for part of the returns to general skills in both green and non-green jobs. Overall, we show that green jobs require broader bundles of valuable skills per ad, and these bundles explain a non-trivial share of the premium. However, the evidence does

[26]For the low-carbon counterpart, results are again similar. See Appendix Table E.20.

not suggest that these general skills are rewarded more highly in green roles. The next subsection quantifies the contribution of this channel more formally using an Oaxaca-Blinder decomposition.

5.3 Oaxaca-Blinder decomposition

The previous subsection showed that green jobs require broader bundles of valuable skills, but that these skills are not rewarded more highly in green than in non-green vacancies. Even so, richer skill bundles can still contribute to the green wage premium through an endowment effect. We now quantify that contribution using a standard Oaxaca-Blinder decomposition (Fortin et al., 2011). This decomposition also allows us to more precisely isolate the average return to green tasks, net of differences in skill composition and firm rents.

To implement the decomposition in a setting with multiple fixed effects, we first partial out the fixed effects from either equation 1 or equation 2 - excluding the green job indicator - by regressing log wages and each skill variable (s_k) on the full set of fixed effects.[27] For each variable $v \in \{w, s_1, \ldots, s_K\}$ we estimate:

$$v_{it} = \boldsymbol{\gamma}^\top \mathbf{d}_{it} + \tilde{v}_{it}, \tag{3}$$

where $\mathbf{d}_{it}$ collects the fixed effects and $\tilde{v}_{it}$ is the residual net of all controls.[28] This residualisation isolates within-cell variation in wages and skills, ensuring that the decomposition is not driven by differences in the occupational, regional, or firm composition of green and non-green job postings.

We then estimate separate weighted OLS regressions of residualised log-wages $\tilde{w}_i$ on the vector of residualised skill dummies $\tilde{\mathbf{s}}_i = (\tilde{s}_{1i}, \ldots, \tilde{s}_{Ki})^\top$ for green ($h = g$) and non-green ($h = ng$) vacancies:

$$\tilde{w}_i \;=\; \tilde{\mathbf{x}}_i^\top \boldsymbol{\beta}^h + \alpha^h + \varepsilon_i^h, \qquad h \in \{g,\, ng\}, \tag{4}$$

where observations are weighted by by country-specific ISCO 3-digit employment levels, as in our main analysis. The estimated coefficients $\hat{\boldsymbol{\beta}}^h$ capture the within-cell returns to each skill family in green and non-green jobs.

Letting $\Delta^g \equiv \bar{\tilde{w}}^g - \bar{\tilde{w}}^{ng}$ denote the mean residual wage gap between green and non-green postings, the Oaxaca-Blinder approach decomposes Δ^g as:

$$\Delta^g \;=\; \underbrace{\left(\bar{\tilde{\mathbf{x}}}^g - \bar{\tilde{\mathbf{x}}}^{ng}\right)^\top \hat{\boldsymbol{\beta}}^{ng}}_{\text{Endowments}} + \underbrace{\bar{\tilde{\mathbf{x}}}^{ng\top}\left(\hat{\boldsymbol{\beta}}^g - \hat{\boldsymbol{\beta}}^{ng}\right) + \left(\hat{\alpha}^g - \hat{\alpha}^{ng}\right)}_{\text{Coefficients}} + \underbrace{\left(\bar{\tilde{\mathbf{x}}}^g - \bar{\tilde{\mathbf{x}}}^{ng}\right)^\top \left(\hat{\boldsymbol{\beta}}^g - \hat{\boldsymbol{\beta}}^{ng}\right)}_{\text{Interaction}}. \tag{5}$$

[27] The part-time dummy is treated symmetrically to the skill variables in the decomposition: its residual is obtained by projecting it on the same fixed effects and it enters the group-specific regressions alongside the skill dummies.

[28] The fixed effects included are: NUTS-2, country-by-year, ISCO 3-digit and, depending on the specification, firm.

The endowment component measures how much of Δ^g is explained by green jobs requiring a different bundle of general skills than non-green jobs, holding returns constant at non-green levels. The coefficient component captures differences in the returns to those skills across the two groups, evaluated at the non-green skill endowment, and can therefore be interpreted as a skill price effect. The interaction term captures the joint contribution of differences in both endowments and returns. By construction, the three components sum exactly to the green wage premium Δ^g. Of particular interest is the difference in intercepts, $(\hat{\alpha}^g - \hat{\alpha}^{ng})$, which captures the unexplained (or discriminatory) residual wage gap after accounting for observable skill bundles and is therefore our best proxy for the average return to green task. This residual can be compared directly with the coefficient δ^g estimated in equations 1 and 2. To account for sampling variability arising from the multi-step estimation procedure, and for arbitrary dependence within labour market cells, we compute standard errors using a cluster bootstrap with 200 replications, resampling at the NUTS2 × ISCO-2 level. This propagates uncertainty from both the residualization stage and the group-specific wage regressions into the final decomposition estimates.

Table 7: Oaxaca Blinder decomposition of the green wage premium into skill endowments and residual return to green tasks

	(1)		(2)	
	Coef.	(SE)	Coef.	(SE)
Green Job	0.0568***	(0.0041)	0.0235***	(0.0023)
Non-green Job	-0.0014	(0.0018)	-0.0006	(0.0011)
Difference Δ^g	0.0582***	(0.0043)	0.0241***	(0.0025)
Endowments	0.0186***	(0.0011)	0.0063***	(0.0004)
Coefficients	0.0429***	(0.0042)	0.0190***	(0.0025)
Intercept $\hat{\alpha}^g - \hat{\alpha}^{ng}$	0.0428***	(0.0041)	0.0190***	(0.0025)
Interaction	-0.0033***	(0.0011)	-0.0012***	(0.0003)
Country × Year FE	Yes		Yes	
NUTS (2-digits) FE	Yes		Yes	
ISCO (3-digits) FE	Yes		Yes	
Part-time FE	Yes		Yes	
Firm FE	No		Yes	
Observations	15,742,224		15,742,224	

Notes. The table presents a threefold Oaxaca–Blinder decomposition of the green wage premium. The outcome is log wages residualised from fixed effects regressions including country × year, NUTS (2-digit), ISCO (3-digit), and part-time fixed effects; column (2) additionally includes firm fixed effects. The decomposition separates the wage gap into endowments (characteristics), coefficients (returns), and interaction components. The reference group is non-green jobs. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are obtained from 200 cluster bootstrap replications at the NUTS (2-digit) × ISCO (2-digit) level. Number of unique firms: 221,942. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7 presents the main results. In column 1, where wages are residualized without firm fixed effect, the predicted green wage premium is 5.8%. In column 2, where firm fixed effect are also partialled out, the predicted premium falls to 2.4%. The difference between these two estimates reflects the role of firm rents. Notably, these green wage premia are very close to those reported in Table 6, despite the slightly different specification.[29]

The decomposition shows that differences in skill endowments explain a meaningful, but not dominant, share of the premium. In column 1, the skill endowment effect accounts for about one third of the residual wage gap ($0.32 = 0.0186/0.0582$), while the coefficients effect accounts for the remaining two thirds, and the interaction term is small and negative. The same qualitative pattern holds in the specification with firm fixed effects (column 2), where the endowment effect still explains around one quarter of the within-firm green wage premium.

Looking more closely at the coefficient component, the dominant element is the intercept difference, which captures the average return to green tasks. In our preferred specification, with firm fixed effects and skill endowment, this return is equal to 1.9%, only slightly below the 2.2% estimate obtained from equation 2. The small negative interaction term and the near zero coefficient effect for individual skill families are also aligned with Figure 3, which showed that broad skills are generally not rewarded more highly in green jobs. Instead, the endowment effect is driven mainly by management (0.58%) and technical skills (0.36%), consistent with the high prevalence in green vacancies (see Appendix Table E.21).

Overall, the Oaxaca-Blinder decomposition and the regression results paint a coherent picture of the drivers of the green wage premium. Conditional on occupation, region and country-year fixed effects, the premium is about 5.8% (Table 7) to 5.9% (Table 4). Firm rents account for more than half of this gap ($53-59\%$). Differences in observable skill bundles explain a further non-trivial share ($11-13\%$),[30] while the remaining residual - net of a small negative interaction term - is the average return to green task, which is the structural parameter of interest in our analysis. Importantly, this return is approximately $1.9-2.2\%$, which is below the green wage premium estimated in other studies using either OJV data (Bone et al., 2025; Saussay et al., 2026) or occupation-level data (Bluedorn et al., 2023; Kuai et al., 2025; Vona et al., 2019). In comparison with previous studies, our result suggests that accounting for firm rents and differences in skill endowments is essential to get more reliable estimates of the return to green tasks.

[29] Fortin et al. (2011) emphasize that the Oaxaca-Blinder decomposition also provides a check on the functional form of the underlying econometric model. In our application, the key difference relative to equations 1 and 2 is that the skill coefficients are allowed to differ between the treated (green) and control (non-green) group. We minimize the discrepancy between the two approaches by residualizing wages and skills on the same set of fixed effects, thereby imposing that regional, occupational, country-year, and firm fixed effects enter symmetrically in both groups.

[30] Using the Oaxaca-Blinder decomposition, the contribution of skill endowments can be expressed relative to the baseline premium as $0.0063/0.0582$, where 0.0063 is the coefficient of the endowment effect in the specification with firm fixed effect and 0.0582 is the green wage premium is the specification without firm fixed effect. A very similar order of magnitude is obtained from the regression-based comparison in Table 4. a back-to-the-envelope calculation gives $0.13 = 0.008/0.059$, where 0.008 is the difference between results of column 4, with only firm fixed effects, and of column 6, with also skill endowment.

6 Conclusion

A central question for the green transition is whether labour markets generate sufficient wage incentives for workers to acquire the skills required for decarbonizing the economy. We study this question using online job vacancy data for EU countries over 2018–2023, developing a transparent LLM-based approach to identify green jobs from vacancy-level skill requirements. We provide the first decomposition of the green wage premium into its underlying components: firm rents, skill complexity, and the average return to green tasks.

Our descriptive analysis reveals that green job shares in Europe rose from 2.6% to 3.6% over the sample period, consistently above comparable US estimates, which is consistent with Europe's more ambitious climate policy agenda. Green employment is heterogeneous across regions, occupations, and industries, with the fastest growth occurring among high-skilled occupations and in sectors that have been the main beneficiaries of the EU Green Deal.

Turning to wages, we estimate an overall green wage premium of 5.5% within 3-digit occupations. However, this estimate is not readily interpretable as the average return to green tasks, as it reflects several components. Firm-effects accounts for roughly one half of the premium, and the broader bundles of general non-green skills required by green jobs explain a further one tenth. The residual return to green tasks, our structural parameter of interest, is approximately 2%. By contrast, we find limited evidence that non-monetary job attributes, such as purpose-oriented or ethical content, are more prevalent in green jobs or that they affect the estimated premium. Our results also indicate that the decomposition matters: studies that do not account for firm effects and skill complexity risk overstating the returns to green tasks and, consequently, the strength of market-based adjustment.

These findings have direct implications for the green transition. If the wage signal for acquiring green skills is this modest - an order of magnitude smaller than recent estimates of the return to acquiring AI skills (Bone et al., 2025), to working in finance (Marin & Vona, 2023), or to working in fossil fuel jobs (Saussay et al., 2026) - market forces alone may be insufficient to drive the skill reallocation that decarbonization demands. This strengthens the case for active training and reskilling policies to complement the wage incentives that labour markets currently provide.

Unfortunately, funding for retraining and reskilling remain weak or inexistent in most green recovery packages approved or discussed around the world (OECD, 2021). Further research is required to assess the role of green educational programs on occupational choices of new graduates.

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A Lightcast data: Coverage and representativeness

We assess the representativeness of Lightcast data by comparing it to the LFS employment statistics. As expected, the Lightcast data over-represent some groups relative to others. In particular, large countries, service-sector jobs, and high- and middle-skill occupations are generally over-represented. For example, Table A.2 and Figure A.1 show that Germany and France account for 29% and 24% of all Lightcast ads, respectively, but only 17% and 9% of employment across the 29 countries in the LFS. Other over-represented countries include the Netherlands, Belgium, Sweden, Austria, Switzerland, Denmark and Ireland. By contrast, Italy, Poland, Spain, Czech, Romania and other smaller countries are under-represented in the vacancy data relative to their employment shares.

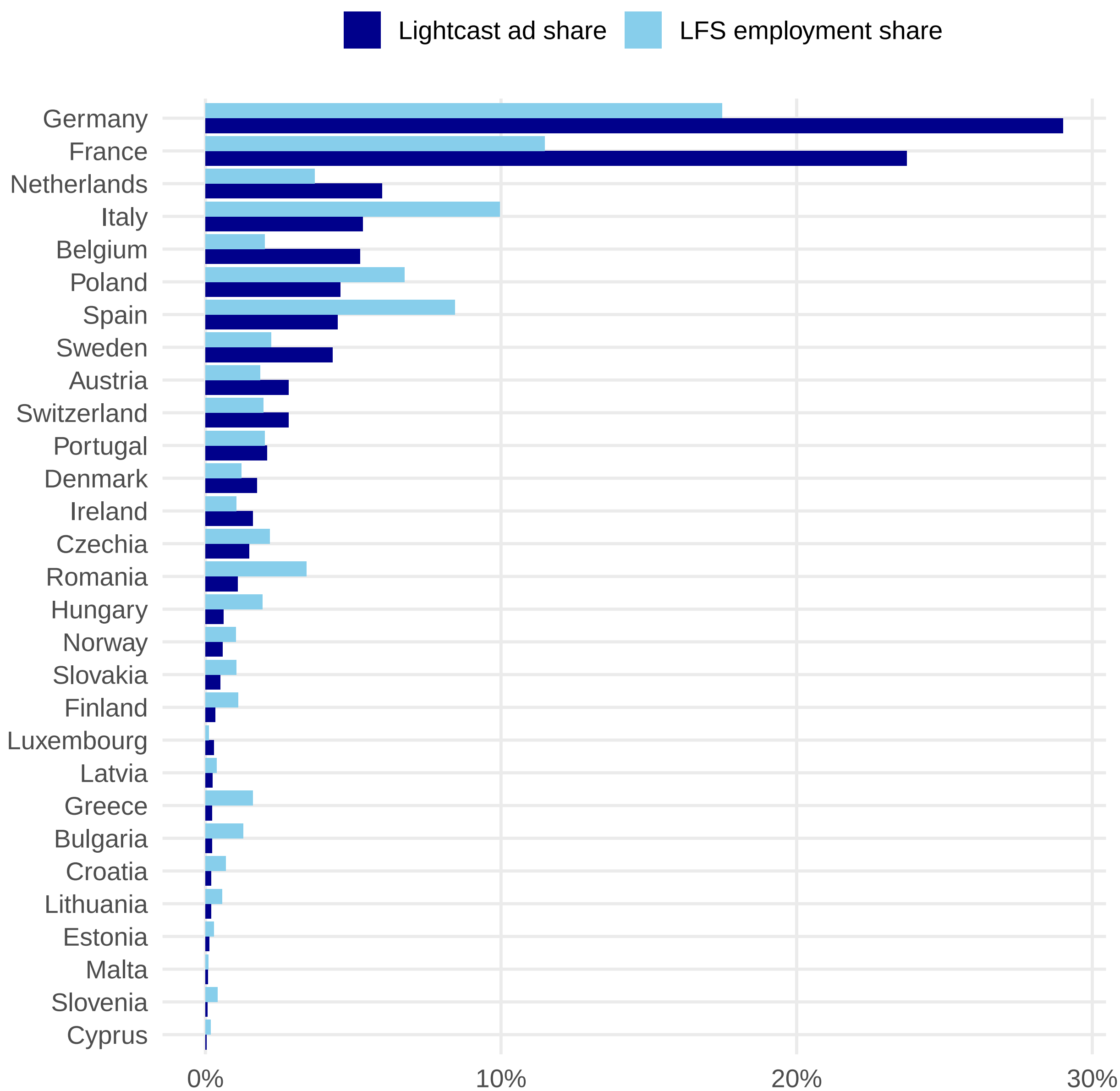
A similar pattern emerges across occupations. Table A.3 and Figure A.2 compare 2-digit ISCO shares in the Lightcast and LFS data. Occupations such as sales workers (ISCO 52), business administration professionals and associate professionals (ISCO 24 and 33), and ICT professionals (ISCO 25) are over-represented in Lightcast, as are many other high- and middle-skill occupations. By contrast, teaching professionals (ISCO 23), cleaners and helpers (ISCO 91), and skilled agricultural workers (ISCO 61) are relatively under-represented. Nevertheless, even for under-represented occupations, the sample still contains many tens of thousands of observations, which gives us sufficient statistical power to examine green job shares and wage gaps within broad occupational groups.

Table A.1: Missing value shares for key variables

		Share missing				
	Total ads	Wage	Occupation	NUTS2	Sector	Firm
Full sample	194,930,996	86.4%	7.8%	22.4%	72.6%	32.7%
Wage sample	25,330,683	0.0%	0.0%	16.2%	72.3%	28.7%

Notes: The wage sample cover ads that have non-missing wage and occupation, are in one of the twelve countries of interest, and have wage outliers trimmed.

Figure A.1: Country shares: Lightcast vs. Labour Force Surveys



Notes:

This figure depicts by country, job ads as a share of all ads as well as employment as a share of total employment, as given by Labour Force Surveys. Countries include EU27 members plus Norway and Switzerland and are ordered by total number of ads in the Lightcast data.

Table A.2: Country shares and ad counts: Lightcast vs. Labour Force Surveys

Country	Ad count	Unweighted ad share	LFS employment share
Germany	56,557,498	29.01%	17.47%
France	46,236,646	23.72%	11.47%
Netherlands	11,655,736	5.98%	3.69%
Italy	10,392,853	5.33%	9.96%
Belgium	10,192,217	5.23%	2.01%
Poland	8,912,245	4.57%	6.74%
Spain	8,722,249	4.47%	8.45%
Sweden	8,393,143	4.31%	2.23%
Austria	5,489,742	2.82%	1.85%
Switzerland	5,473,919	2.81%	1.96%
Portugal	4,055,910	2.08%	2.00%
Denmark	3,396,776	1.74%	1.22%
Ireland	3,127,914	1.60%	1.05%
Czechia	2,892,156	1.48%	2.17%
Romania	2,130,599	1.09%	3.42%
Hungary	1,194,711	0.61%	1.93%
Norway	1,127,961	0.58%	1.03%
Slovakia	996,167	0.51%	1.05%
Finland	659,989	0.34%	1.10%
Luxembourg	560,712	0.29%	0.12%
Latvia	471,126	0.24%	0.38%
Greece	449,732	0.23%	1.60%
Bulgaria	430,897	0.22%	1.28%
Croatia	376,302	0.19%	0.70%
Lithuania	373,059	0.19%	0.56%
Estonia	243,770	0.13%	0.28%
Malta	179,864	0.09%	0.11%
Slovenia	146,805	0.08%	0.41%
Cyprus	90,298	0.05%	0.18%

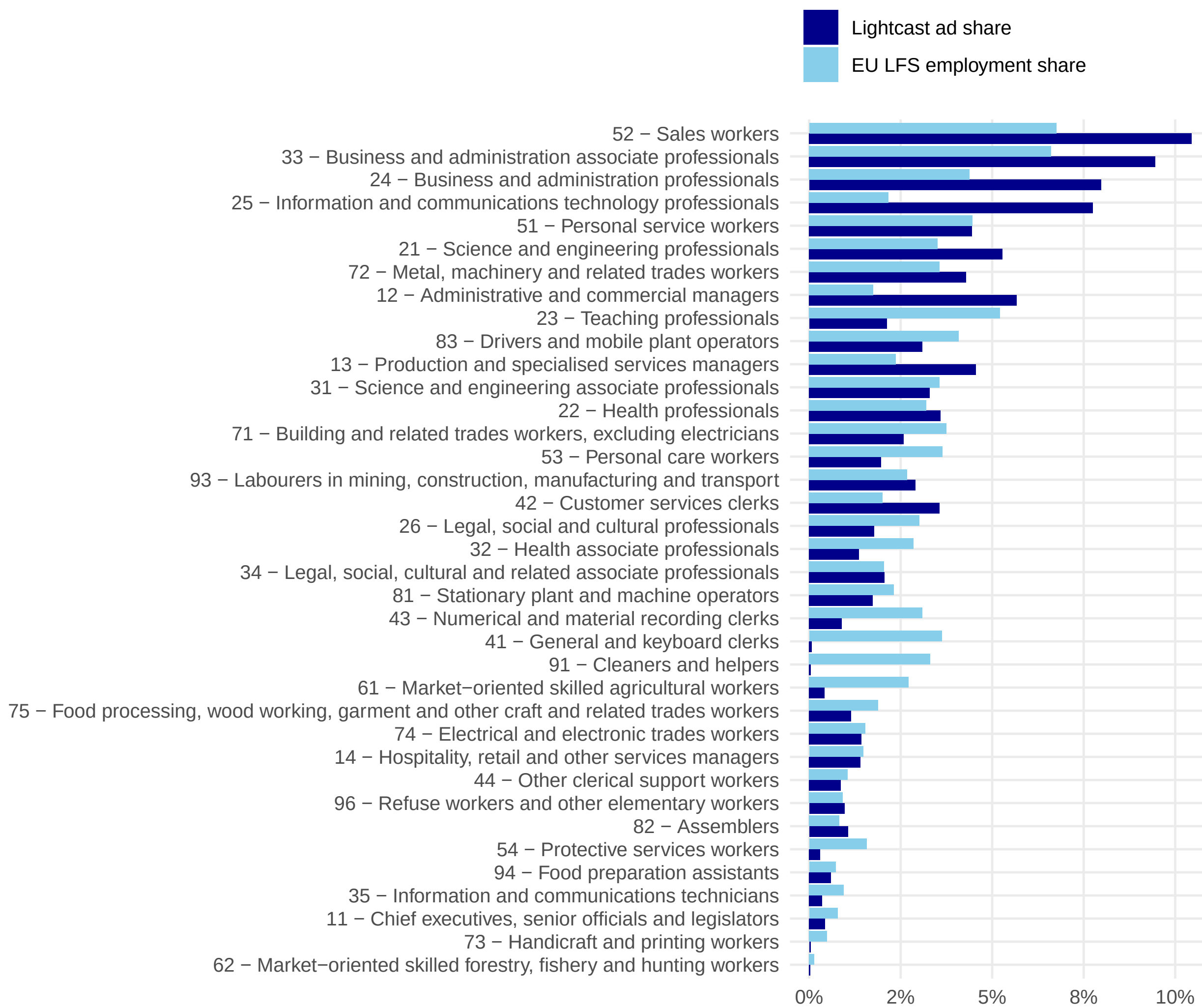
Notes: This table shows the number of job ads for each country (2018-2023) in levels and as a share of total ads across all 29 countries (EU27 plus Norway and Switzerland). The fourth column shows each country's share of total employment across all 29 countries (avg. 2018-2023) as given by Labour Force Surveys.

Table A.3: 2-digit ISCO occupation shares and ad counts: Lightcast vs. Labour Force Surveys

2-digit ISCO Occupation	Ad count	Unweighted ad share	LFS share
11 - Chief executives, senior officials and legislators	773,593	0.4%	0.8%
12 - Administrative and commercial managers	10,187,443	5.7%	1.8%
13 - Production and specialised services managers	8,177,209	4.6%	2.4%
14 - Hospitality, retail and other services managers	2,508,142	1.4%	1.5%
21 - Science and engineering professionals	9,492,711	5.3%	3.5%
22 - Health professionals	6,440,528	3.6%	3.2%
23 - Teaching professionals	3,808,044	2.1%	5.2%
24 - Business and administration professionals	14,319,375	8.0%	4.4%
25 - Information and communications technology professionals	13,927,494	7.8%	2.2%
26 - Legal, social and cultural professionals	3,182,576	1.8%	3.0%
31 - Science and engineering associate professionals	5,925,217	3.3%	3.6%
32 - Health associate professionals	2,454,692	1.4%	2.9%
33 - Business and administration associate professionals	16,983,066	9.5%	6.6%
34 - Legal, social, cultural and related associate professionals	3,709,215	2.1%	2.0%
35 - Information and communications technicians	636,033	0.4%	0.9%
41 - General and keyboard clerks	128,521	0.1%	3.6%
42 - Customer services clerks	6,406,383	3.6%	2.0%
43 - Numerical and material recording clerks	1,595,684	0.9%	3.1%
44 - Other clerical support workers	1,546,369	0.9%	1.1%
51 - Personal service workers	7,999,304	4.5%	4.5%
52 - Sales workers	18,758,205	10.4%	6.8%
53 - Personal care workers	3,523,526	2.0%	3.6%
54 - Protective services workers	548,096	0.3%	1.6%
61 - Market-oriented skilled agricultural workers	751,090	0.4%	2.7%
62 - Market-oriented skilled forestry, fishery and hunting workers	51,179	0.0%	0.1%
71 - Building and related trades workers, excluding electricians	4,648,538	2.6%	3.8%
72 - Metal, machinery and related trades workers	7,696,035	4.3%	3.6%
73 - Handicraft and printing workers	70,128	0.0%	0.5%
74 - Electrical and electronic trades workers	2,568,242	1.4%	1.5%
75 - Food processing, wood working, garment and other craft and related trades workers	2,070,185	1.2%	1.9%
81 - Stationary plant and machine operators	3,120,189	1.7%	2.3%
82 - Assemblers	1,903,703	1.1%	0.8%
83 - Drivers and mobile plant operators	5,562,426	3.1%	4.1%
91 - Cleaners and helpers	82,356	0.0%	3.3%
93 - Labourers in mining, construction, manufacturing and transport	5,228,226	2.9%	2.7%
94 - Food preparation assistants	1,080,651	0.6%	0.7%
96 - Refuse workers and other elementary workers	1,735,004	1.0%	0.9%

Notes: This table depicts job ads (total number and share of all ads) for each 2-digit ISCO occupation across all EU27 countries plus Norway and Switzerland. For comparison, the LFS share column shows each occupation's share of total employment across these countries according to Labour Force Surveys.

Figure A.2: 2-digit ISCO occupation shares: Lightcast vs. Labour Force Surveys



Notes: For each 2-digit ISCO occupation, this figure depicts job ads as a share of all ads as well as employment as a share of total employment, as given by Labour Force Surveys. Includes EU27 countries plus Norway and Switzerland.

B Green skills selection algorithm: implementation details

B.1 LLM classification protocol: stages, ensemble aggregation, and manual review

This appendix details the implementation of the LLM-based classification procedure summarised in Section 2.2. The procedure is applied separately to two sets of items: the 22,814 Lightcast skills tagged as Specialised or Certification, and all 1,894 Lightcast Specialised Occupation titles. We exclude Common, Software, and Language skills before any LLM call, as these categories are too general to serve as vacancy-level green indicators. They capture generic competencies, software proficiency, or language requirements rather than job-specific task content. For each set of items, the classification proceeds through three automated prompting stages, followed by ensemble aggregation across seven frontier models and a manual review of ambiguous cases. Table B.1 summarises the inputs, admissible outputs, and forwarding rule at each stage. The full prompt text for both skills and occupations is reported in Appendix B.2.

Table B.1: Three-stage classification protocol

Stage	Inputs	Admissible outputs	Forwarded items
1	Skill title and Lightcast subcategory; specialized occupation title and standardized description. Explicit reference to Commission Delegated Regulation (EU) 2021/2139.	*Climate or Green*; *Not Climate, Not Green.*	Items labeled *Climate or Green.*
2	Title plus description.	*Decarbonization-energy*; *Decarbonization-transport*; *Decarbonization-buildings*; *Decarbonization-industry*; *Climate-CCS*; *Climate-adaptation*; *Climate-general*; *Waste-management*; *Forestry-ecosystem-management*; *Not-climate-nor-green-related.*	Items assigned one of the nine green types.
3	Title plus description.	*Too broad or too vague*; *Specific climate or green.*	Used only as a specificity screen for review and exclusion.

Notes: The same three prompts are applied to skills and to Lightcast Specialized Occupations. Stage 3 is run only for items that receive one of the nine green labels in Stage 2.

Three-stage prompting: In the first stage, each item is presented to the model together with its Lightcast subcategory (for skills) or standardised description (for occupations), and the model is asked whether the item is core and specific to climate change mitigation or adaptation, or to closely related non-climate environmental activities. The prompt explicitly grounds the classification in the Commission Delegated Regulation (EU) 2021/2139 and instructs the model to exclude items that are broadly applicable or required by most jobs. Items labelled “Climate or Green” are forwarded to the second stage.

In the second stage, each forwarded item is assigned to one of nine green activity categories: decarbonisation of energy, transport, buildings, or industry; climate-CCS; climate adaptation; climate-general; waste management; or forestry-ecosystem management. Items that do not fit any of these categories are assigned to a residual "Not-climate-nor-green-related" group. This stage serves as a consistency check on the initial binary screen: a candidate green item must be assignable to a concrete environmental domain, not merely contain loosely environmental language. Items such as Sewage Collection and Disposal, Soil Management, or Reverse Osmosis, which may pass a binary green screen but lack a clear mapping to a specific green activity, are filtered out at this stage.

In the third stage, items that received one of the nine green labels in stage two are subjected to a specificity filter. The model is asked whether the item is "Too broad or too vague" to be characteristic of climate or green activities, or "Specific climate or green." This screen targets items that survived the categorical assignment but whose scope extends well beyond environmental applications — for instance, generic energy or agricultural skills that happen to intersect with green domains but are not specific to them. The stage-three output is not used as an independent classification decision, but enters the ensemble aggregation rule described below.

Model ensemble: Rather than relying on a single model, we run the three-stage prompt sequence across seven frontier (as of November 2025) models: OpenAI GPT-OSS-120B, DeepSeek V3.2, Mistral Large 2512, Meta Llama 4 Maverick, Anthropic Claude Sonnet 4.5, OpenAI GPT-5.1, and Google Gemini 2.5 Pro. Each model is run once at each stage with deterministic settings (temperature set to 0 and top-p equal to 1). All prompts are zero-shot, and the set of admissible outputs is closed by construction at every stage. We adopt a multi-model ensemble because recent evidence shows that LLM classifications can vary materially across models and prompting choices, while aggregation across models improves reliability in both economics applications and classification settings more broadly (Ludwig et al., 2025; Schoenegger et al., 2024; Trust & Minghim, 2024).

Aggregation and decision rules. For item i (where i is a given skill or occupation), let g_i denote the number of models that assign one of the nine green types in Stage 2, and let b_i denote the number of models that return *Too broad or too vague* in Stage 3. We apply the following decision rule:

1. If $g_i \leq 2$, we exclude the item automatically.
2. If $g_i = 3$, we send the item to manual review as a potential false negative.
3. If $g_i = 4$ and $b_i \geq 2$, if $g_i = 5$ and $b_i \geq 3$, or if $g_i = 6$ and $b_i \geq 4$, we send the item to manual review because the detailed label is weak relative to the broadness screen.
4. All other items with $g_i \geq 4$ are retained automatically as green.

Manual review: Items flagged under rules 2 and 3 above are reviewed independently by the five coauthors. An item is retained as green when at least four of the five reviewers agree it belongs to one of the nine green categories, and excluded when at least four agree it does not. For occupations, we apply a more conservative criterion: even among items that pass the ensemble vote or manual review, we retain only titles for which the coauthor team judges that every job classified under the title would plausibly involve green task content. This yields a final set of 17 fully green specialised occupations, compared with 20 that passed the ensemble vote alone.

Final classification: The procedure yields 591 green specialised skills and 17 fully green specialised occupations (Tables D5 and D.6). A vacancy is green if its skill vector contains at least one green skills or if its Lightcast Specialized Occupation belongs to the set of 17 fully green occupations. The low-carbon indicator is created directly from the final green type. Items labeled *Waste-management* or *Forestry-ecosystem-management* are coded as green but not low-carbon; all other green types are coded as low-carbon.

Broader and narrower classification variants:

- Narrow variant: retain only skills classified as green by at least 6 LLMs, while none considered them too broad (*i.e.* $g_i \geq 6$ and $b_i = 0$)
- Broad variant: include any skill classified as green by at least 3 LLMs (*i.e.* $g_i \geq 3$)

B.2 LLM classification prompts

B.2.1 Skill classification prompts

Stage 1. *You're considering skills in job ads, and you want to identify skills that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such as ecosystem protection, green forestry or waste management. To this end, you must follow the criteria defined by the European Union's Taxonomy - more specifically, the Commission Delegated Regulation (EU) 2021/2139.*

Consider the skill "skill" in category "subcategory". Would you consider it a core skill for climate change mitigation or adaptation, or non-climate green activities?

Remember it cannot broad or generic and has to be specific to climate change mitigation or adaptation or non-climate environmental protection (e.g. forestry or waste management). In particular if most jobs require that skill, you cannot consider it specific to climate or specific green non-climate. Conversely, make sure to include the skills that contribute directly to the reduction of greenhouse gas emissions, decarbonization of energy and power generation (e.g. renewable energy, smart grids, battery storage), transportation (e.g. electric vehicles, public transportation, rail), buildings (e.g. weatherization, insulation, heat pumps, energy efficiency), industry (e.g. clean hydrogen production) and agriculture, and adaptation to a changing climate and management of climate-related weather disasters (e.g. storms and floods).

You should simply answer with "Climate or Green", or "Not Climate, Not Green". No additional text.

Stage 2. *You're considering skills in job ads, and you want to identify skills that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such as ecosystem protection, green forestry or waste management. Consider the skill "skill" in category "subcategory", defined as "description". Classify it in one of the categories below. It is very important that if the occupation title is broad, and not specific to decarbonized energy, decarbonized transportation, decarbonized industry, decarbonized or reduced buildings energy use, adaptation to climate change, waste management, forestry or ecosystem management, you should label it as Not-climate-nor-green-related.*

- Decarbonization-energy: this skill is essential and specific to the reduction of greenhouse gas emissions, related to energy generation, transmission or distribution - Decarbonization-transport: this skill is essential and specific to the reduction of greenhouse gas emissions related to transportation, including public transportation - Decarbonization-buildings: this skill is essential and specific to the decarbonization of buildings, e.g. housing, house appliances or related end-user applications - Decarbonization-industry: this skill is essential and specific to the reduction of greenhouse gas emissions related to industrial processes and production - Climate-CCS: this skill is essential and specific to the capture, storage, sequestration or disposal of greenhouse gases. Make sure this is not actually a fossil-fuel related occupation. - Climate-adaptation: this skill is essential and specific to adaptation to climate change adaptation - Climate-general: this skill contains the word 'Climate', 'Greenhouse gas' or 'Emissions' and does not fit in any of the above categories. - Waste-management: this skill is helping with waste (solid or water) management but is not specific to climate change mitigation or adaptation - Forestry-ecosystem-management: this skill is helping with forest and ecosystem management but is not specific to climate change mitigation or adaptation. - Not-climate-nor-green-related: this skill is not climate-specific or green-specific enough to be classified in any of the above categories.

Simply answer with "Decarbonization-energy", "Decarbonization-transport", "Decarbonization-buildings", "Decarbonization-industry", "Climate-CCS", "Climate-adaptation", "Climate-general", "Waste-management", "Forestry-ecosystem-management", "Not-climate-nor-green-related". No additional text.

Stage 3. *You're considering skills in job ads, and you want to identify skills that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such as ecosystem protection, green forestry or waste management. Consider the skill "skill" in category "subcategory", defined as "description".*

Is this skill broadly applicable, beyond the specific pursuit of climate or green objectives (e.g. sewage systems, generic agricultural science, generic energy-related technologies, etc.), or too vague to be characteristic? If that is the case, you should label the skill as "Too broad or too vague". Otherwise label it with "Specific climate or green".

Reply only with "Too broad or too vague" or "Specific climate or green".

B.2.2 Occupation classification prompts

Stage 1. *You're considering occupation titles, and you want to identify occupations that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such* *as ecosystem protection, green forestry or waste management. To this end, you must follow the criteria defined by the European Union's Taxonomy - more specifically, the Commission Delegated Regulation (EU) 2021/2139.*

Consider the occupation "{occ}". {occ_desc}. Would you consider it a core occupation for climate change mitigation or adaptation, or non-climate green activities?

Remember it cannot broad or generic and has to be specific to climate change mitigation or adaptation or non-climate environmental protection (e.g. forestry or waste management). In particular, every single job classified under a climate-core occupation must also be considered as contributing directly to climate change mitigation or adaptation. Make sure to include the core occupations that contribute directly to the decarbonization of power generation (e.g. smart grids and battery storage), transportation (e.g. electric vehicles and public transportation), buildings (e.g. weatherization and heat pumps), industry (e.g. clean hydrogen production) and agriculture.

Every green non-climate occupation has to actively contribute to environmental preservation or sustainable development.

You should simply answer with "Climate or Green", or "Not Climate, Not Green". No additional text.

Stage 2. *You're considering occupation titles, and you want to identify occupations that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such as ecosystem protection, green forestry or waste management. Consider the occupation "{occ}", where {occ_desc}. Classify it in one of the categories below. It is very important that if the occupation title is broad, and not specific to decarbonized energy, decarbonized transportation, decarbonized industry, decarbonized or reduced buildings energy use, adaptation to climate change, waste management, forestry or ecosystem management, you should label it as Not-climate-nor-green-related.*

- Decarbonization-energy: this occupation is essential and specific to the reduction of greenhouse gas emissions, related to energy generation, transmission or distribution - Decarbonization-transport: this occupation is essential and specific to the reduction of greenhouse gas emissions related to transportation, including public transportation - Decarbonization-buildings: this occupation is essential and specific to the decarbonization of buildings, e.g. housing, house appliances or related end-user applications - Decarbonization-industry: this occupation is essential and specific to the reduction of greenhouse gas emissions related to industrial processes and production - Climate-CCS: this occupation is essential and specific to the capture, storage, sequestration or disposal of greenhouse gases. Make sure this is not actually a fossil-fuel related occupation. - Climate-adaptation: this occupation is essential and specific to adaptation to climate change adaptation - Climate-general: this occupation contains the word 'Climate', 'Greenhouse gas' or 'Emissions' and does not fit in any of the above categories. - Waste-management: this occupation is helping with waste (solid or water) management but is not specific to climate change mitigation or adaptation - Forestry-ecosystem-management: this occupation is helping with forest and ecosystem management but is not specific to climate change mitigation or adaptation. - Not-climate-nor-green-related: this occupation is not climate-specific or green-specific enough to be classified in any of the above categories.

Simply answer with "Decarbonization-energy", "Decarbonization-transport", "Decarbonization-buildings", "Decarbonization-industry", "Climate-CCS", "Climate-adaptation", "Waste-management", "Forestry-ecosystem-

management", "Not-climate-nor-green-related". No additional text.

Stage 3. *You're considering occupation titles, and you want to identify occupations that are specific to climate change mitigation or adaptation, and those that are linked to other non-climate green activities such as ecosystem protection, green forestry or waste management. Consider the occupation "{occ}", where {occ_desc}.*

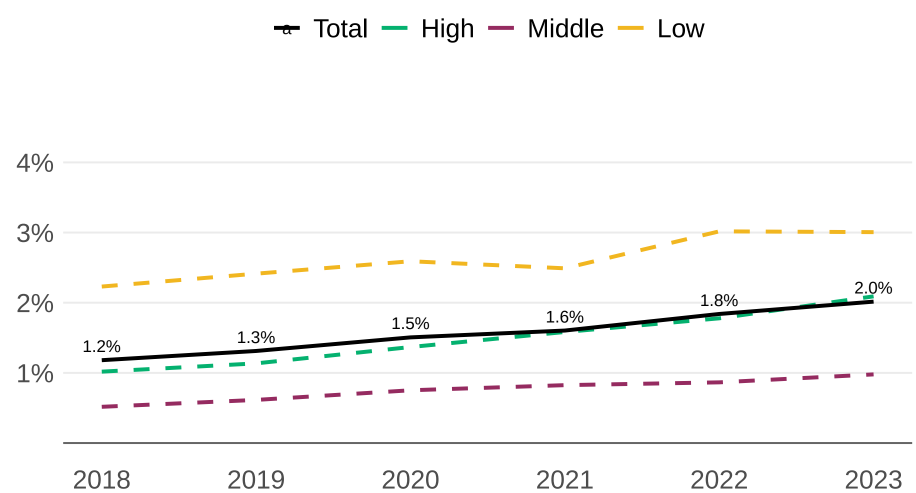
Is this occupation title broad, beyond the specific pursuit of climate or green objectives (e.g. sewage systems, generic agricultural science, generic energy-related technologies, etc.), or too vague to be characteristic? If that is the case, you should label the occupation title as "Too broad or too vague". Otherwise label it with "Specific climate or green".

Reply only with "Too broad or too vague" or "Specific climate or green".

C Descriptive evidence: additional tables and figures

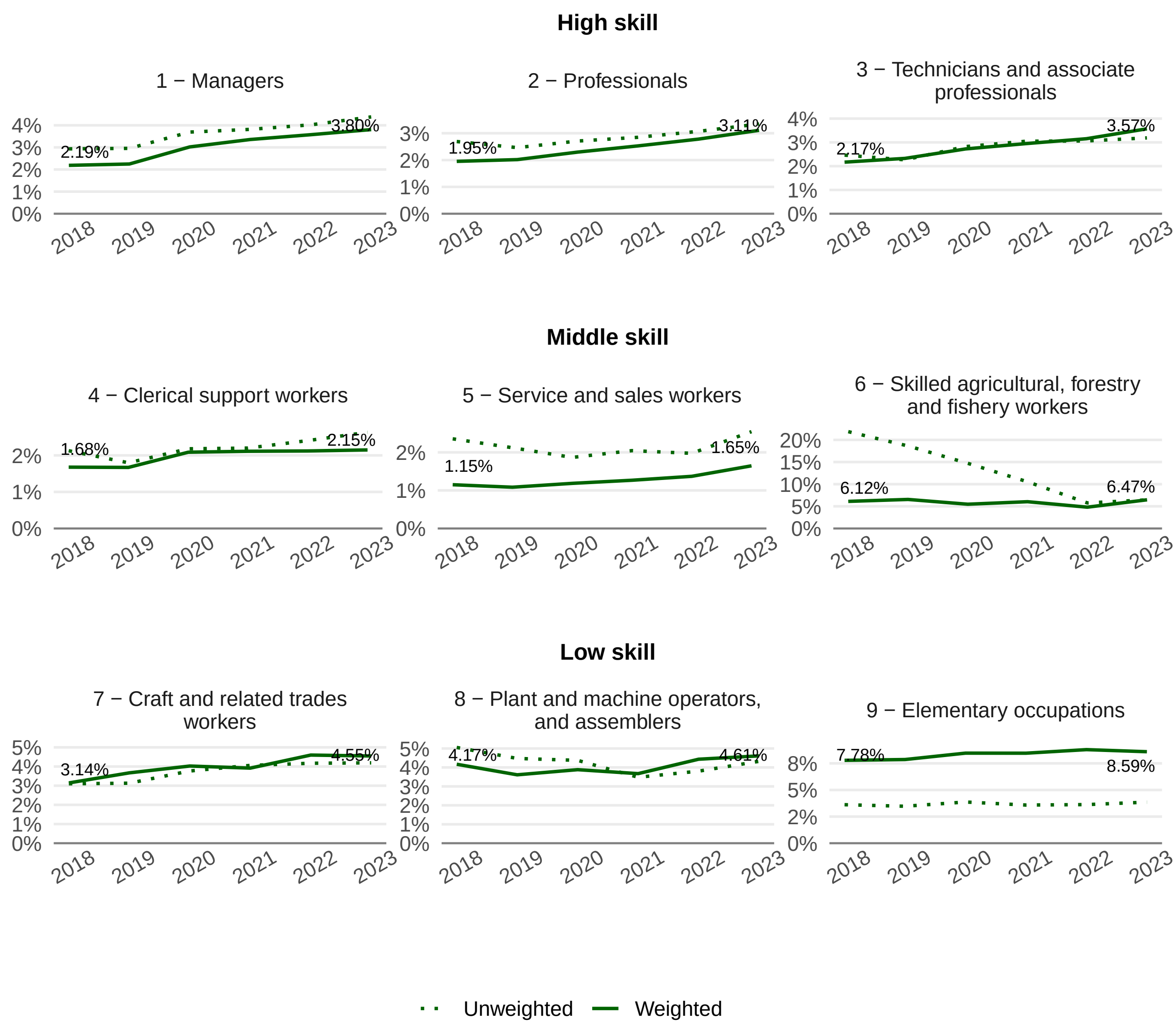
C.1 Occupational distribution

Figure C.1: Evolution of low-carbon job shares by skill level, 2018-2023



Notes. Job shares weighted by country-specific ISCO 3-digit occupation employment. Includes EU27 countries plus Norway and Switzerland. High skill covers ISCO 1-digit occupations 1, 2, and 3; middle skill covers occupations 4, 5, 6; low skill covers occupations 7, 8, 9. Annotations indicate aggregate (weighted) low-carbon job shares for each sample year.

Figure C.2: Green job shares by 1-digit ISCO occupation



Notes: Job shares weighted by country-specific ISCO 3-digit occupation employment. Includes EU27 countries plus Norway and Switzerland. Annotations indicate weighted green job shares in 2018 and 2023.

Table C.1: Green job shares by 1-digit ISCO occupation

		Green job share	
1-digit ISCO Occupation	Total ads	Weighted	Unweighted
High skill			
1 - Managers	21,646,387	3.35%	3.85%
2 - Professionals	51,170,728	2.66%	2.96%
3 - Technicians and associate professionals	29,708,223	3.06%	2.93%
Middle skill			
4 - Clerical support workers	9,676,957	2.05%	2.32%
5 - Service and sales workers	30,829,131	1.45%	2.18%
6 - Skilled agricultural, forestry and fishery workers	802,269	6.37%	10.79%
Low skill			
7 - Craft and related trades workers	17,053,128	4.14%	3.89%
8 - Plant and machine operators, and assemblers	10,586,318	4.30%	4.12%
9 - Elementary occupations	8,126,237	8.98%	3.70%

Notes: Total ads refers to the total number of ads of across all countries for the corresponding 1-digit ISCO occupation. Countries includes EU27 plus Norway and Switzerland. Weighted ad shares use country-level 3-digit ISCO employment as weights. Unweighted ad shares are calculated directly from the sample of job ads.

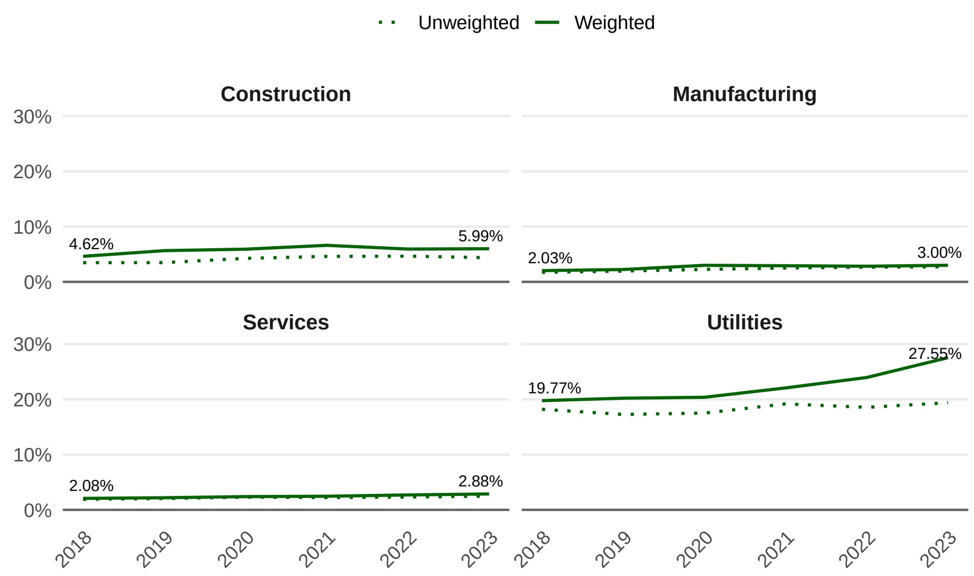
Table C.2: Green job shares by 2-digit ISCO occupation

2-digit ISCO Occupation	Total ads	Green job share	
		Weighted	Unweighted
High skill			
11 - Chief executives, senior officials and legislators	773,593	2.75%	2.70%
12 - Administrative and commercial managers	10,187,443	3.25%	3.62%
13 - Production and specialised services managers	8,177,209	4.72%	4.67%
14 - Hospitality, retail and other services managers	2,508,142	1.79%	2.49%
21 - Science and engineering professionals	9,492,711	6.19%	5.67%
22 - Health professionals	6,440,528	1.73%	1.55%
23 - Teaching professionals	3,808,044	1.53%	1.65%
24 - Business and administration professionals	14,319,375	2.70%	2.63%
25 - Information and communications technology professionals	13,927,494	2.58%	2.74%
26 - Legal, social and cultural professionals	3,182,576	1.59%	1.82%
31 - Science and engineering associate professionals	5,925,217	6.57%	5.94%
32 - Health associate professionals	2,454,692	2.48%	2.69%
33 - Business and administration associate professionals	16,983,066	1.85%	2.02%
34 - Legal, social, cultural and related associate professionals	3,709,215	1.77%	2.52%
35 - Information and communications technicians	636,033	1.96%	2.60%
Middle skill			
41 - General and keyboard clerks	128,521	1.38%	1.55%
42 - Customer services clerks	6,406,383	2.07%	2.53%
43 - Numerical and material recording clerks	1,595,684	2.24%	2.18%
44 - Other clerical support workers	1,546,369	1.44%	1.66%
51 - Personal service workers	7,999,304	1.18%	1.34%
52 - Sales workers	18,758,205	1.51%	2.70%
53 - Personal care workers	3,523,526	1.15%	1.16%
54 - Protective services workers	548,096	2.54%	3.15%
61 - Market-oriented skilled agricultural workers	751,090	5.66%	10.75%
62 - Market-oriented skilled forestry, fishery and hunting workers	51,179	18.35%	11.42%
Low skill			
71 - Building and related trades workers, excluding electricians	4,648,538	3.97%	4.99%
72 - Metal, machinery and related trades workers	7,696,035	2.33%	2.41%
73 - Handicraft and printing workers	70,128	1.56%	1.52%
74 - Electrical and electronic trades workers	2,568,242	13.06%	7.87%
75 - Food processing, wood working, garment and other craft and related trades workers	2,070,185	1.41%	2.06%
81 - Stationary plant and machine operators	3,120,189	1.97%	2.23%
82 - Assemblers	1,903,703	1.90%	2.11%
83 - Drivers and mobile plant operators	5,562,426	5.66%	5.86%
91 - Cleaners and helpers	82,356	1.82%	1.73%
93 - Labourers in mining, construction, manufacturing and transport	5,228,226	1.89%	2.34%
94 - Food preparation assistants	1,080,651	1.64%	1.56%
96 - Refuse workers and other elementary workers	1,735,004	34.96%	9.22%

Notes: Total ads refers to the total number of ads of across all countries for the corresponding 2-digit ISCO occupation. Countries include the EU27 plus Norway and Switzerland. Weighted ad shares use country-level 3-digit ISCO employment as weights. Unweighted ad shares are calculated directly from the sample of job ads.

C.2 Sectoral distribution

Figure C.3: Green job shares by NACE sector

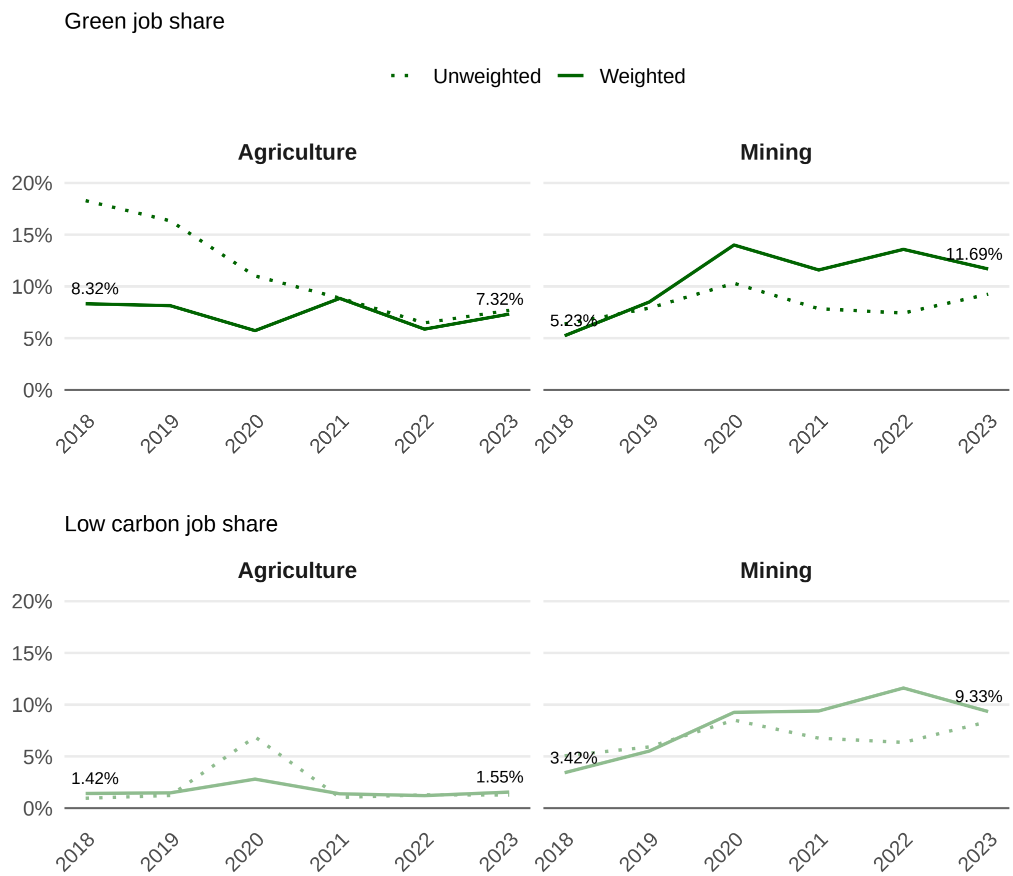


Notes: Job shares weighted by country-specific ISCO 3-digit occupation employment. Includes EU27 countries plus Norway and Switzerland.

Figure C.4: Low-carbon job shares by NACE sector

Notes: Job shares weighted by country-specific ISCO 3-digit occupation employment. Includes EU27 countries plus Norway and Switzerland.

Figure C.5: Green and low-carbon job shares by NACE primary sector



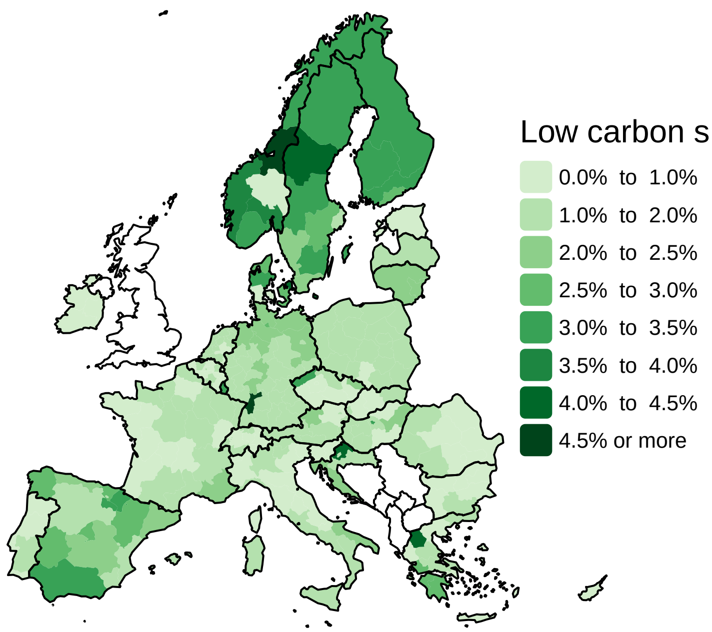
Notes: Job shares weighted by country-specific ISCO 3-digit occupation employment. Includes EU27 countries plus Norway and Switzerland.

C.3 Country and regional variation

Figure C.6: Green job shares by country, 2018-2023

Notes: Plot titles indicate the ISO3 country code and the green job share for the entire sample period. Weighted green job shares use country-specific 3-digit ISCO employment (averaged over 2018-2023) as weights.

Figure C.7: Low carbon ad share by NUTS2 region, 2018-2023



Notes: This map depicts the country-level 3-digit ISCO weighted share of ads that are low carbon for NUTS2 regions. Countries not in the sample are shown in white.

C.4 Wage distribution

Table C.3: Descriptive statistics for advertised salaries

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Green	20,767,568	0.027	0.161	0	0	0	0	1
Low carbon	20,767,568	0.015	0.121	0	0	0	0	1
All occupations and sectors								
Salary	20,767,568	35,280.86	19,507.59	3,666.00	23,683.00	30,450.00	40,665.00	500,000.00
Salary (PT)	2,928,054	33,200.95	15,304.88	4,564.00	23,423.00	29,651.75	39,038.00	466,822.50
Salary (firm FE sample)	15,742,224	35,608.27	18,841.36	3,666.00	24,021.00	30,788.00	41,178.50	500,000.00
Salary (PT, firm FE sample)	2,159,665	33,806.91	15,173.33	4,610.00	23,683.00	30,200.00	39,580.00	466,822.50
By occupation								
Salary (ISCO 1)	1,726,629	46,905.31	24,550.29	3,666.00	31,577.00	41,953.00	56,930.50	500,000.00
Salary (ISCO 2)	4,394,627	44,296.99	23,890.05	3,666.00	29,929.00	39,580.50	52,401.00	500,000.00
Salary (ISCO 3)	3,069,116	36,331.09	18,958.56	3,666.00	25,310.00	32,532.00	42,201.00	500,000.00
Salary (ISCO 4)	1,203,977	32,108.83	16,726.88	3,666.00	23,423.00	29,186.00	35,785.00	458,084.00
Salary (ISCO 5)	4,634,693	28,737.01	14,649.84	3,666.00	21,413.00	25,310.00	31,577.00	493,896.50
Salary (ISCO 6)	107,801	29,949.27	16,502.99	3,666.00	22,735.00	27,109.50	32,532.00	494,672.00
Salary (ISCO 7)	2,316,021	32,213.38	13,434.52	3,666.00	24,669.50	29,821.00	36,435.50	458,084.00
Salary (ISCO 8)	1,920,431	29,767.27	12,193.75	3,666.00	22,848.00	27,977.50	33,833.00	458,084.00
Salary (ISCO 9)	1,394,273	27,748.98	12,554.01	3,666.00	22,242.00	25,293.00	30,059.50	458,084.00
By sector								
Salary (Agriculture)	29,158	33,679.42	20,816.24	6,392.00	22,242.00	26,712.00	38,387.50	336,334.00
Salary (Construction)	363,257	30,279.92	14,570.18	3,666.00	22,735.00	25,657.00	32,531.50	439,178.00
Salary (Manufacturing)	559,227	32,397.06	16,452.77	3,666.00	23,269.00	28,240.00	36,435.50	433,756.00
Salary (Mining)	3,761	34,777.37	14,049.74	9,109.00	26,567.50	33,833.00	41,727.00	166,913.00
Salary (Services)	4,701,380	34,939.47	19,804.86	3,666.00	23,423.00	29,322.00	39,900.50	500,000.00
Salary (Utilities)	161,584	28,710.90	13,943.57	5,040.50	21,453.00	22,735.00	31,881.00	379,537.00

Notes: The table reports descriptive statistics for green job indicators and advertised annual salaries at the job-ad level. Salary refers to the posted annual gross salary in euros, deflated with the HICP with 2018 as base. "Salary" refers to salary of part-time/full-time employment status, while "Salary (PT)" refers to salary of part-time employment status. Green and Low carbon are dummy variables equal to one if the job posting is classified as green or low-carbon, respectively. Statistics are reported for the full sample, by 1-digit ISCO occupation groups, and by broad sector. N denotes the number of job advertisements. p25, p50, and p75 correspond to the 25th, 50th (median), and 75th percentiles of the salary distribution.

D Cross-validation with other green skills definitions

This appendix provides a detailed comparison of our LLM-based green job classification with two external benchmarks: the ESCO green skills taxonomy and Lightcast's experimental green skill classification. We compare the three approaches along four dimensions: scope and coverage, country-level green job shares, occupation-level green job shares, and the evolution of green employment over time.

Scope and coverage: The three classifications differ substantially in what they count as green. Our classification is grounded in the EU Taxonomy Regulation 2021/2139, which defines conditions under which economic activities qualify as contributing to climate change mitigation or adaptation while causing no significant harm to other environmental objectives. This yields a relatively narrow definition focused on climate-related task content. The ESCO green skills taxonomy adopts the broader Cedefop definition of green skills as “the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment” (Cedefop, 2012). This encompasses domains not covered by our source text, including biodiversity, animal welfare, sustainable consumption, environmental education, sustainable tourism, agriculture, and nuclear energy. Climate adaptation, conversely, is included only in our classification. Lightcast's experimental list was constructed manually using ESCO, O*NET, and Lightcast's own taxonomy as inputs, and is closest to ours in scope and coverage.

These differences in scope translate into large differences in the number of skills classified as green. Using crosswalks provided by Lightcast to map ESCO skills to Lightcast skills, we identify 1,198 Lightcast skills classified as green under the ESCO green label, compared with 424 under our classification.[31]

Table D.1 compares the top green skills under each classification. The two approaches share substantial common ground in core domains, including renewable energy, recycling, environmental protection, pollution prevention, and ecosystem science. The main source of disagreement reflect differences in scope. Skills included in our own classification but not ESCO's includes several public transport skills, silviculture, nuclear power, and electric vehicles. Skills classified under ESCO but not our approach include several very common and broadly applicable skills, such as packaging and labelling, tourism, enthusiasm, biology, and lean manufacturing, whose inclusion reflects ESCO's wider definition of greenness.[32].

Country-level comparison: Table D.2 compares green job shares across the 29 countries in our sample under our definition and ESCO's definition. Unsurprisingly given the much higher number of Lightcast skills defined as green by ESCO versus by our approach, we find that green job shares are much higher according to ESCO's definition of green skills relative to our own definition. On aggregate across our 29-country sample, the 3-digit ISCO employment-weighted green job share is 3.3% by our own definition, and 13.2% by the ESCO definition. Despite the large differences in levels, however, the two definitions produce similar country rankings. Both identify Germany, Denmark, Finland and Norway as having relatively high green job shares, and Czech Republic, Estonia, Slovakia and Cyprus as having among the lowest. Table D.3 repeats this comparison for the Lightcast classification, where the agreement is even closer: the aggregate Lightcast green job

[31] Lightcast provided two experimental crosswalks. The first maps one ESCO skill to one Lightcast skill and covers almost all ESCO green skills, identifying 370 Lightcast skills. The second maps one Lightcast skill to one ESCO skill; it only includes about 43% of the ESCO green skills but has wide Lightcast skills coverage, raising the tltal to 1,198. Table D.4 compares green job shares using only the first crosswalk versus both.

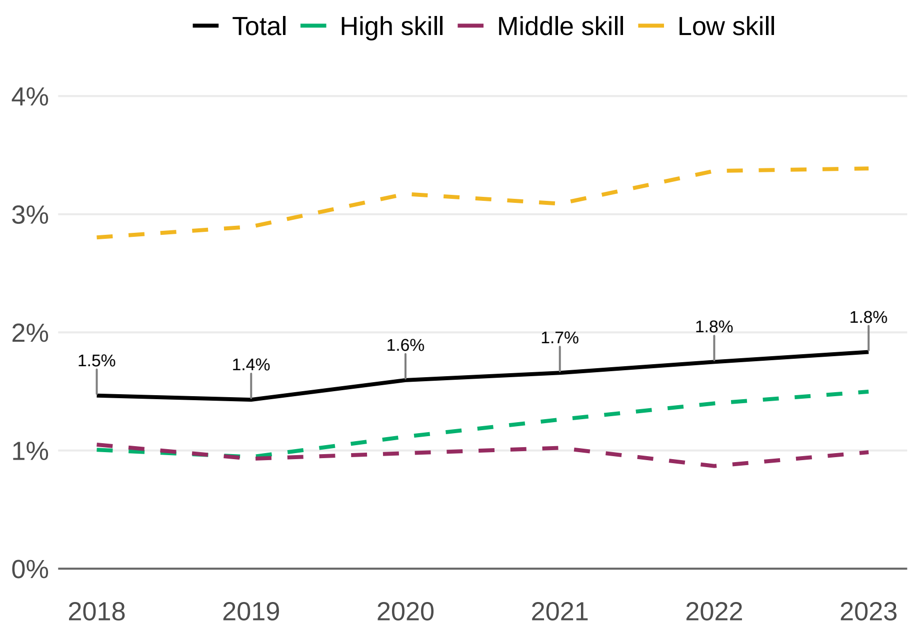
[32] The Lightcast skill "Enthusiasm" maps to the ESCO green skills "inspire enthusiasm for nature" and "exude enthusiasm during the action sessions", highlighting the inherent difficulty of mapping Lightcast skills to ESCO skills, which are often very task-specific

share is 2.3%, and country-level patterns closely track ours. The main exception is that Lightcast assigns a notably higher green share to Finland and Slovakia, and a lower share to France, relative to our classification.

Occupation-level comparison: Figure D.3 plots 3-digit ISCO occupation green job shares under our own definition on the x-axis against those under the ESCO-definition on the y-axis. The slope of the best fit line is 0.437, indicating that on average across all occupations, our definition leads to higher green job shares compared to the ESCO definition. However, this aggregate relationship is driven by just a couple of occupations that we define as very green relative to ESCO's definition - Forestry and Related Workers (ISCO 621) and Refuse Workers (ISCO 961) have green job shares of 40% and 100% respectively, while the ESCO definition leads to a green job share of 38.4% and 39.1%, respectively. Outside of these outliers, the ESCO definition generally leads to much higher green job shares, especially for Manufacturing Labourers (below 1% under our definition versus over 50% under ESCO) and Life Science Professionals (19% versus 60%), as well as fishery and agriculture as well as physical and earth scientists. Figure D.4 plots the same comparison for the Lightcast classification. The correlation is substantially tighter (employment-weighted slope of 0.75), consistent with the closer alignment in scope. The main exceptions are refuse workers and locomotive drivers (higher under our definition) and veterinarians and life science professionals (higher under Lightcast).

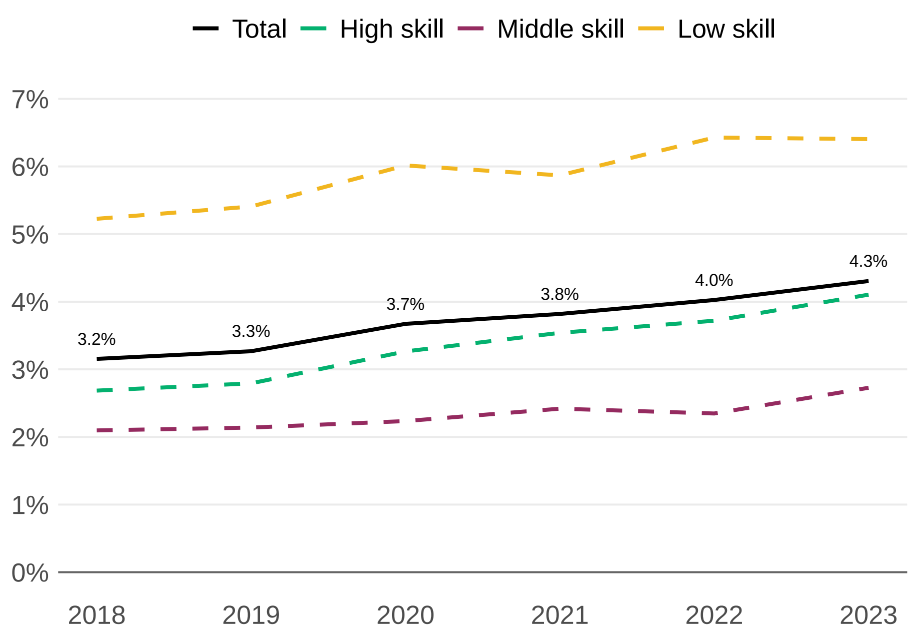
Evolution over time: Figure D.5 shows the evolution of green job shares from 2018 to 2023 under our classification and the ESCO definition. Both display a gradual upward trend: our weighted green share rises from 2.6% to 3.6%, while ESCO's rises from 11.7% to 13.2%. Figure D.6 shows a similar comparison with the Lightcast classification, which also trends upward from 1.8% to 2.6%. Finally, as already discussed in the main text, the green job share exhibits similar patterns using either the narrow (Figure) or broad (Figure D.2) definitions of green jobs. Overall, the parallel trajectories across independently constructed taxonomies suggest that the growth in green employment documented in Section 3 is not an artefact of our particular classification choices.

Figure D.1: Evolution of green job shares (narrow definition), 2018-2023



Notes. This figure includes EU27 countries plus Norway and Switzerland, and shows green job shares (narrow definition) calculated using country-specific ISCO 3-digit occupation employment as weights. The annotations indicate aggregate green job shares (i.e. for all skill levels together). High skill covers ISCO 1-digit occupations 1, 2, and 3; middle skill covers occupations 4, 5, 6; low skill covers occupations 7, 8, 9.

Figure D.2: Evolution of green job shares (broad definition), 2018-2023



Notes. This figure includes EU27 countries plus Norway and Switzerland, and shows green job shares (broad definition) calculated using country-specific ISCO 3-digit occupation employment as weights. The annotations indicate aggregate green job shares (i.e. for all skill levels together). High skill covers ISCO 1-digit occupations 1, 2, and 3; middle skill covers occupations 4, 5, 6; low skill covers occupations 7, 8, 9.

Table D.1: Top green skills by classification: This paper versus ESCO

Lightcast skill	Ad count	ESCO skill(s)
Both classifications		
Recycling	500,184	*Educate on recycling regulations, Maintain recycling records, Inspect recycling procedures, Research recycling grant opportunities, Develop recycling programs, Identify new recycling opportunities, Train staff on recycling programs, Follow recycling collection schedules*
Environmental Protection	321,397	*Protection from natural elements, Implement environmental protection measures*
Pollution Prevention	299,617	*Adopt ways to reduce pollution, Advise on pollution prevention, Pollution prevention, Prevent marine pollution*
Renewable Energy	269,485	*Offshore renewable energy technologies, Renewable energy technologies*
Ecosystem Science	194,600	*Ecosystems*
Only ESCO green classification		
Packaging And Labeling	2,559,735	*Pack leather, Check bottles for packaging, Ensure correct goods labelling*
Tourism	2,188,624	*Teach tourism principles, Develop tourism products, Support local tourism, Participate in tourism events, Support community-based tourism, Develop tourism destinations, Tourist resources of a destination for further development, Report touristic facts, Collect tourist information, Develop tourist information materials, Geographical areas relevant to tourism*
Enthusiasm	2,136,740	*Inspire enthusiasm for nature, Exude enthusiasm during the action sessions*
Biology	1,039,715	*Teach biology, Biology*
Lean Manufacturing	927,738	*Lean manufacturing*
Only this paper's green classification		
Commuter Rail	284,400	*Rail infrastructure*
Silviculture	262,546	*Floriculture*
Public Transport	257,451	*Promote public transport*
Rail Transport	216,866	*Freight transport methods*
Electric Vehicles	129,400	*Electric drives*

Notes: This table lists the top five skills (by number of ads) classified as green according to (i) both this paper and the ESCO green skills collection (version 1.1.1), (ii) only the ESCO green skills collection, and (iii) only this paper. We map ESCO skills to Lightcast skills using crosswalks supplied by Lightcast.

Table D.2: Cross-validation with ESCO green skills

	Unweighted green job share		Weighted green job share	
	ESCO	This paper	ESCO	This paper
Total	**12.5%**	**3.1%**	**13.2%**	**3.3%**
Occupation skill levels				
High	12.4%	3.1%	12.7%	2.9%
Middle	11.5%	2.4%	13.0%	2.1%
Low	14.0%	3.9%	14.1%	5.1%
Countries				
Austria	10.9%	2.6%	11.0%	2.8%
Belgium	12.2%	2.5%	12.1%	2.8%
Bulgaria	12.3%	1.3%	13.7%	3.2%
Switzerland	11.1%	2.3%	11.1%	2.4%
Cyprus	8.6%	0.8%	11.9%	1.9%
Czechia	2.8%	0.5%	2.4%	1.0%
Germany	12.1%	3.7%	13.0%	4.3%
Denmark	14.1%	5.7%	13.4%	5.8%
Spain	12.1%	3.4%	14.1%	3.8%
Estonia	7.5%	0.9%	6.2%	1.9%
Finland	18.7%	4.8%	15.0%	4.6%
France	13.1%	3.2%	13.1%	3.1%
Greece	14.1%	1.4%	15.3%	2.5%
Croatia	13.5%	2.1%	16.7%	3.7%
Hungary	17.3%	3.7%	21.8%	7.0%
Ireland	16.0%	2.3%	16.6%	2.6%
Italy	13.3%	2.0%	13.7%	2.3%
Lithuania	9.9%	1.0%	12.3%	2.2%
Luxembourg	12.0%	2.2%	11.2%	2.3%
Latvia	10.3%	1.0%	14.4%	3.5%
Malta	9.8%	1.0%	11.6%	1.7%
Netherlands	14.6%	3.0%	14.4%	2.8%
Norway	20.6%	6.6%	16.5%	4.6%
Poland	10.7%	2.0%	11.7%	2.0%
Portugal	12.0%	1.8%	12.8%	2.2%
Romania	11.4%	1.5%	14.0%	2.7%
Slovakia	14.6%	1.6%	10.9%	2.3%
Slovenia	11.8%	1.4%	10.5%	1.6%
Sweden	14.4%	3.8%	14.5%	4.2%

Notes: Jobs are classified as green if they have at least one ESCO green skill (ESCO version 1.1.1). Uses the ESCO to Lightcast and Lightcast to ESCO skills crosswalks supplied by Lightcast. Weighted green job shares use country-specific 3-digit ISCO employment as weights.

Table D.3: Cross-validation with Lightcast green skills

	Unweighted green job share		Weighted green job share	
	Lightcast	This paper	Lightcast	This paper
Total	**2.4%**	**3.1%**	**2.3%**	**3.3%**
Occupation skill levels				
High	2.7%	3.1%	2.7%	2.9%
Middle	1.6%	2.4%	1.5%	2.1%
Low	2.3%	3.9%	2.6%	5.1%
Countries				
Austria	2.3%	2.6%	2.3%	2.8%
Belgium	2.0%	2.5%	1.9%	2.8%
Bulgaria	2.9%	1.3%	3.4%	3.2%
Switzerland	2.2%	2.3%	2.1%	2.4%
Cyprus	0.8%	0.8%	1.6%	1.9%
Czechia	0.8%	0.5%	0.7%	1.0%
Germany	2.9%	3.7%	2.8%	4.3%
Denmark	4.3%	5.7%	4.1%	5.8%
Spain	2.4%	3.4%	2.9%	3.8%
Estonia	1.5%	0.9%	1.3%	1.9%
Finland	6.0%	4.8%	4.7%	4.6%
France	1.8%	3.2%	1.7%	3.1%
Greece	2.4%	1.4%	1.8%	2.5%
Croatia	2.4%	2.1%	1.8%	3.7%
Hungary	4.6%	3.7%	6.0%	7.0%
Ireland	1.9%	2.3%	1.6%	2.6%
Italy	1.3%	2.0%	1.3%	2.3%
Lithuania	2.7%	1.0%	2.4%	2.2%
Luxembourg	3.0%	2.2%	2.8%	2.3%
Latvia	2.5%	1.0%	3.6%	3.5%
Malta	1.2%	1.0%	1.3%	1.7%
Netherlands	2.3%	3.0%	2.0%	2.8%
Norway	6.6%	6.6%	4.3%	4.6%
Poland	2.3%	2.0%	1.8%	2.0%
Portugal	1.6%	1.8%	1.4%	2.2%
Romania	1.8%	1.5%	1.6%	2.7%
Slovakia	4.1%	1.6%	2.6%	2.3%
Slovenia	2.3%	1.4%	1.7%	1.6%
Sweden	3.7%	3.8%	3.7%	4.2%

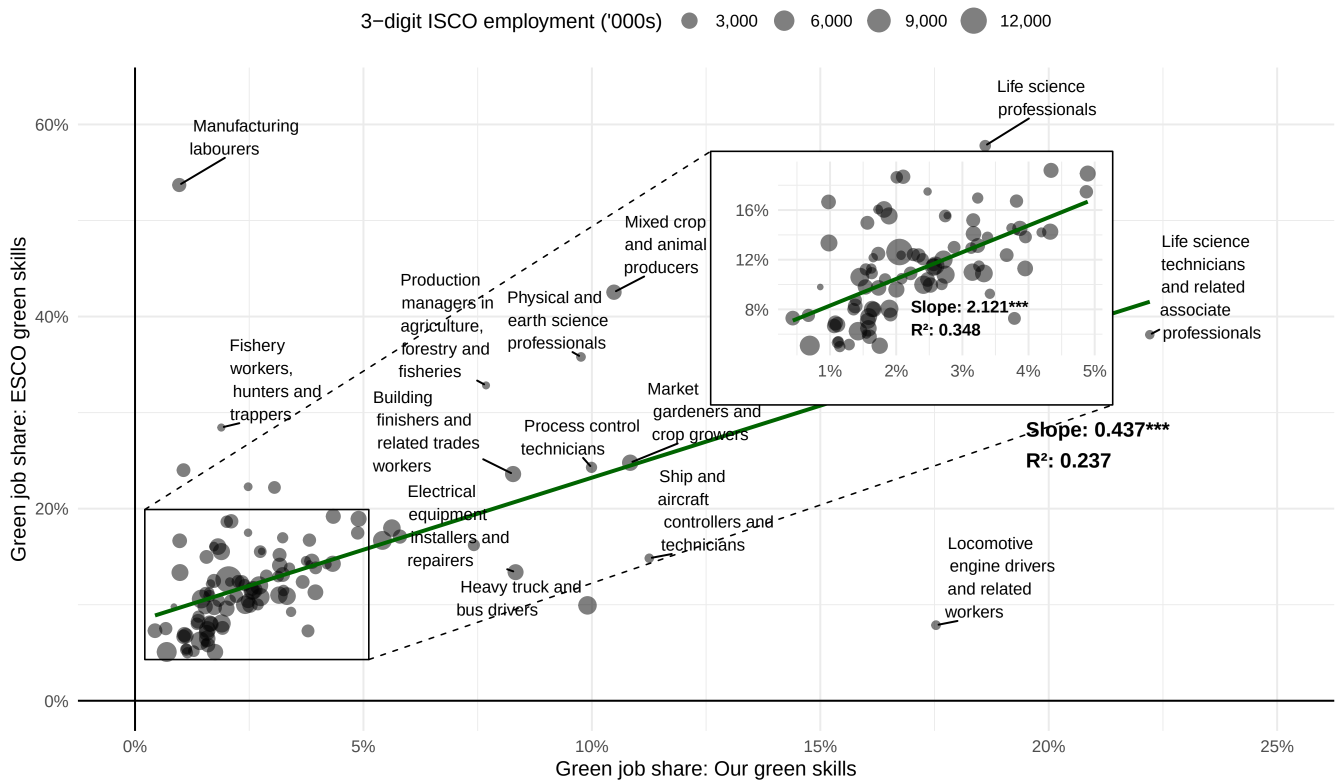
Notes: Jobs are classified as green if they have at least one skill from Lightcast's own list (or our list) of green skills. Weighted green job shares use country-specific 3-digit ISCO employment as weights.

Table D.4: ESCO green job shares: 1 versus both crosswalks with Lightcast skills

	Unweighted green job share		Weighted green job share	
	ESCO2LOT	Both crosswalks	ESCO2LOT	Both crosswalks
Total	9.2%	12.5%	10.1%	13.2%
Occupation skill levels				
High	8.6%	12.4%	9.2%	12.7%
Middle	9.1%	11.5%	10.4%	13.0%
Low	11.3%	14.0%	11.7%	14.1%
Countries				
Austria	7.4%	10.9%	7.7%	11.0%
Belgium	9.9%	12.2%	9.9%	12.1%
Bulgaria	7.7%	12.3%	9.3%	13.7%
Switzerland	7.5%	11.1%	7.6%	11.1%
Cyprus	7.2%	8.6%	10.6%	11.9%
Czechia	1.8%	2.8%	1.6%	2.4%
Germany	9.3%	12.1%	10.1%	13.0%
Denmark	9.2%	14.1%	8.9%	13.4%
Spain	9.4%	12.1%	10.8%	14.1%
Estonia	5.1%	7.5%	4.3%	6.2%
Finland	12.2%	18.7%	10.2%	15.0%
France	8.9%	13.1%	8.9%	13.1%
Greece	10.7%	14.1%	13.3%	15.3%
Croatia	8.4%	13.5%	11.4%	16.7%
Hungary	12.1%	17.3%	17.4%	21.8%
Ireland	13.0%	16.0%	13.2%	16.6%
Italy	11.2%	13.3%	11.8%	13.7%
Lithuania	6.0%	9.9%	9.3%	12.3%
Luxembourg	7.5%	12.0%	7.0%	11.2%
Latvia	6.3%	10.3%	10.8%	14.4%
Malta	8.2%	9.8%	10.1%	11.6%
Netherlands	12.4%	14.6%	12.4%	14.4%
Norway	14.3%	20.6%	12.1%	16.5%
Poland	8.1%	10.7%	9.7%	11.7%
Portugal	9.9%	12.0%	10.8%	12.8%
Romania	8.5%	11.4%	11.7%	14.0%
Slovakia	9.5%	14.6%	7.7%	10.9%
Slovenia	8.4%	11.8%	8.1%	10.5%
Sweden	7.2%	14.4%	7.5%	14.5%

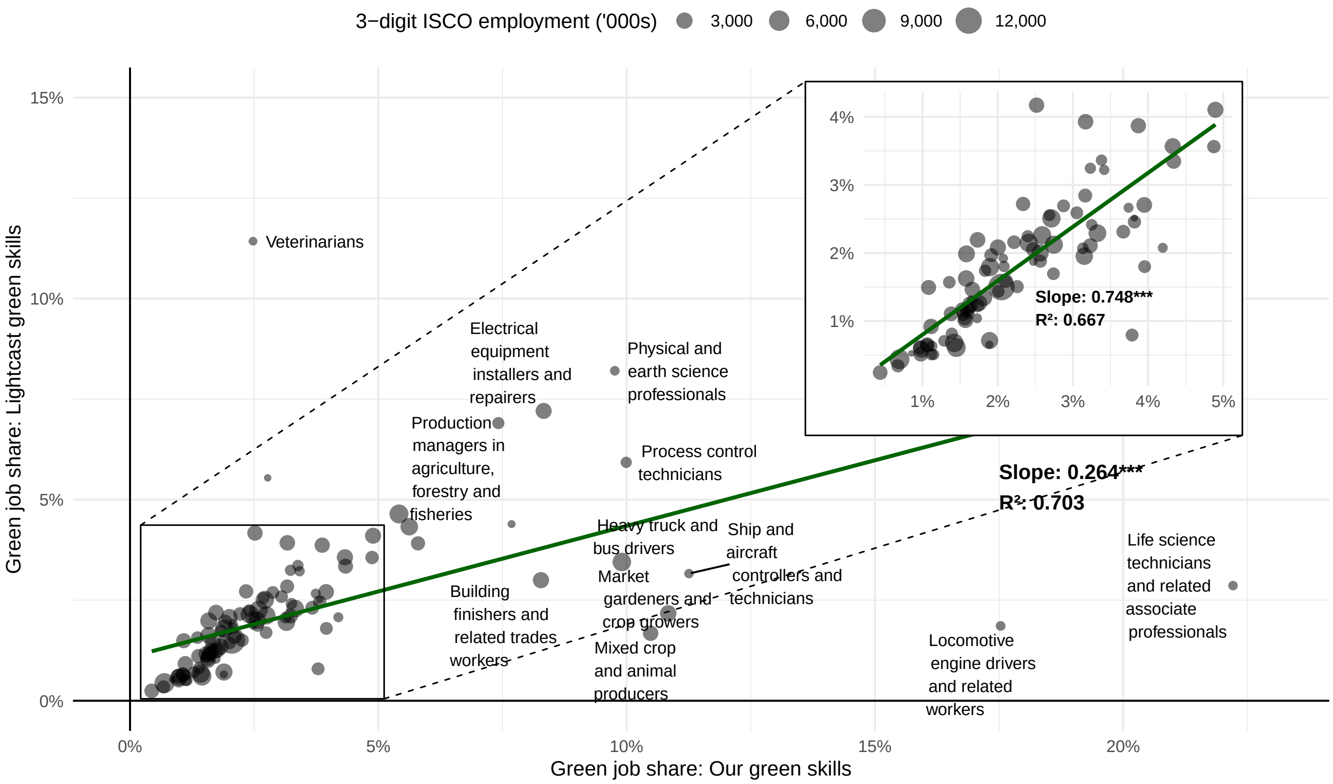
Notes: Jobs are classified as green if they have at least one ESCO green skill (ESCO version 1.1.1). "ESCO2LOT" columns use the ESCO to Lightcast skills crosswalk supplied by Lightcast; "Both crosswalks" use this crosswalk as well as the Lightcast to ESCO crosswalk, which increases the number of ESCO-classified Lightcast green skills from 370 to 1198. Weighted green job shares use country-specific 3-digit ISCO employment as weights.

Figure D.3: 3-digit ISCO green job share: This paper versus ESCO green skills



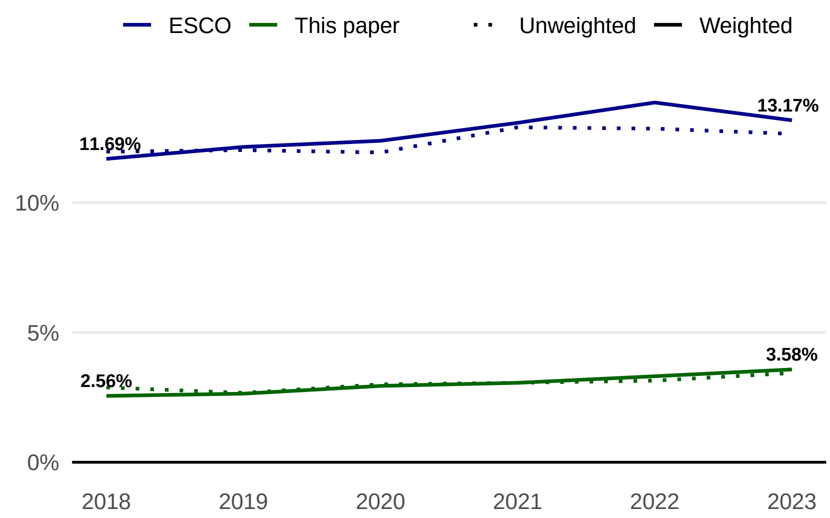
Notes: Jobs are classified as green if they have at least one skill from ESCO's green skills collection (version 1.1.1) or from this paper's own green skills classification. Bubble size reflects total 3-digit ISCO employment across all countries (EU 27 plus Norway and Switzerland) averaged over 2018-2023. The line of best fit is estimated using OLS and weighted by the employment level. For improved readability of the figure, two occupations are not shown because they have very high green job shares in our classification: ISCO 621 (Forestry and related workers, 40% green), and ISCO 961 (Refuse workers, 100% green). With the ESCO green skills definition, these occupations have a green job share of 38.4% and 39.1%, respectively.

Figure D.4: 3-digit ISCO green job share: This paper versus Lightcast



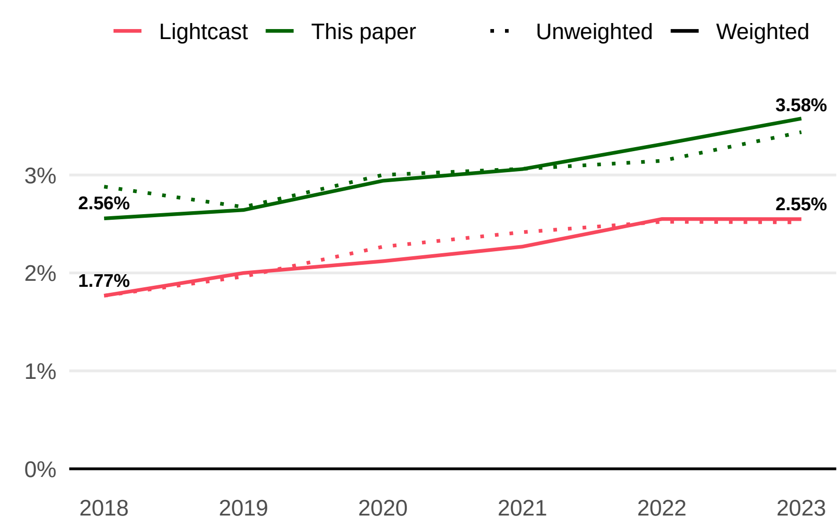
Notes: Jobs are classified as green if they have at least one skill from Lightcast's own list (or our list) of green skills. Bubble size reflects total 3-digit ISCO employment across all countries (EU 27 plus Norway and Switzerland) averaged over 2018-2023. The line of best fit is estimated using OLS and weighted by the employment level. For improved readability of the figure, two occupations are not shown because they have very high green job shares in our classification: ISCO 621 (Forestry and related workers, 40% green), and ISCO 961 (Refuse workers, 100% green). With the Lightcast green skills classification, these occupations have a green job share of 8.9% and 28%, respectively.

Figure D.5: Green job share: this paper versus ESCO green skills, 2018–2023



Notes: Jobs are classified as green if they have at least one skill from from ESCO's green skills collection (version 1.1.1) or from this paper's own green skills classification. Annotations indicate weighted green job shares in 2018 and 2023. Weighted green job shares use country-specific 3-digit ISCO employment as weights. Includes EU27 countries plus Norway and Switzerland.

Figure D.6: Green job share: this paper versus Lightcast, 2018–2023



Notes: Jobs are classified as green if they have at least one skill from Lightcast's own list (or this paper's list) of green skills. Weighted green job shares use country-specific 3-digit ISCO employment as weights. Includes EU27 countries plus Norway and Switzerland.

Table D.5: All green skills (main specification)

Skill	Ad count	Skill	Ad count
Recycling	610,406	Renewable Energy	406,062
Environmental Protection	394,452	Pollution Prevention	371,830
Commuter Rail	337,165	Waste Management	306,464
Public Transport	296,732	Silviculture	276,720
Rail Transport	249,733	Ecosystem Science	233,836
Wastewater	223,578	Electric Vehicles	218,481
Photovoltaics	217,022	Water Treatment	213,928
Energy Management	209,854	Solar Panels	162,630
Nuclear Power	140,093	Circular Economy	133,110
Ecology	132,405	Net Zero	121,306
Sanitary Engineering	116,205	Insulator	105,649
Biodiversity	94,719	Waste Collection	94,542
Biomass	85,825	Solar Energy	85,795
Waste Treatment	78,360	Forestry	77,711
Biogas	75,467	Weatherization	75,035
Retrofitting	73,686	Thermal Insulation	68,658
Wind Power	67,885	Smart Meter Systems	67,660
Rail Operations	65,758	Fuel Cells	63,475
Waste Sorting	59,549	Wind Turbines	57,916
ISO 50001 Standard	55,546	Smart Buildings	54,819
Energy System Transition	53,446	Nuclear Safety	53,196
Landfill	45,758	Environmental Finance	45,320
Water Quality	45,077	Solar Cells	43,903
Cogeneration	43,255	Soil Science	41,157
Grid Connections	40,770	Hydropower	40,014
Biofuels	38,152	Cladding (Construction)	37,873
Climate Change Mitigation	34,603	Waste Minimization	33,786
Arboriculture	33,093	Water Purification	31,962
Energy Conservation	30,157	Greenhouse Gas	29,808
Hybrid Vehicles	28,452	Building Envelope	28,105
Energy Technology	28,023	Concentrix Solar	27,589
Energy Audits	25,701	Energy Management Systems	25,015
Load Management	24,249	Water Resource Management	23,871
Flood Risk Assessments	23,669	Dual Fuel Smart Meter	22,783
Composting	21,934	Bioenergy	21,345
Smart Grid	20,616	Solar Engineering	20,421
Water/Wastewater Engineering	19,199	Levees	18,670
Battery Management	18,535	Leak Detection And Repair	18,085
Sustainable Materials	17,653	Reforestation	17,557
Carbon Footprint Reduction	17,531	Insulation Installation	17,427
Photovoltaic Systems	16,903	Nuclear Engineering	16,535
Clean Technology	16,266	Waste Transport	15,719
Wastewater Treatment Plant	15,691	Hydroelectricity	15,215
Climatology	15,153	Solar Systems	14,993
Green Building	14,737	Sustainable Agriculture	14,509
Incineration	14,439	Smart Meter Installer Core (CMA1)	13,991
Sustainable Design	13,592	Radioactive Waste	13,424
Stormwater Management	13,068	Reverse Logistics	12,933
Battery Technology	12,821	Seawall	12,667
Building Performance	12,423	Water Consumption	12,103
Renewable Energy Systems	11,694	Integrated Pest Management (Agronomy)	11,515
Landscape Ecology	11,504	Climate Policy	11,143
Heat Recovery Ventilation	10,882	Methane	10,879
Wildlife Management	10,736	Soil Conservation	10,716
Hydrogen Production	10,159	District Cooling	10,141
Groundwater Recharge	9,844	Wind Turbine Maintenance	9,562
Energy Modeling	9,529	Biodiesel	9,402

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Table D.5: All green skills (main specification) (Continued)

Skill	Ad count	Skill	Ad count
Energy Saving Products	9,103	Carbon Management	8,981
Climate Variability And Change	8,893	Wildlife Science	8,891
Wind Engineering	8,747	Transfer Station	8,635
Soil Management	8,611	Scrap Metals	8,451
Wind Farming	8,369	Green Infrastructure	8,222
HVAC Design	8,221	Alternative Fuels	8,196
Intelligent Transportation Systems	8,176	Nuclear Fuel Cycle	8,089
Forest Management	7,873	Natural Capital	7,362
Industrial Wastewater	7,346	Renewable Energy Development	7,185
LED Lamps	7,175	Sluice Gate	7,101
Solar Equipment	6,923	Climate Change Adaptation	6,713
Green Chemistry	6,685	Waste Packaging	6,199
Forest Engineering	6,141	Habitat Improvement	6,138
Beekeeping	6,117	Permaculture	6,065
Rangeland Management	6,063	Reverse Osmosis	5,987
Plastic Recycling	5,960	Nuclear Reactor	5,938
Chemical Waste	5,896	Agroecology	5,868
Carbon Accounting	5,740	Marine Science	5,634
Forest Science	5,584	Battery Pack	5,532
Edaphology	5,445	Distributed Generation	5,420
Smart Lighting	5,347	Wildlife Conservation	5,344
Nuclear Fuel	5,344	Sustainable Architecture	5,257
Hazardous Waste Management	5,202	Tree Inventory	5,201
Energy Conservation Measures	5,152	Energy-Efficient Buildings	5,012
Solar Water Heating	4,974	Alternative Energy	4,938
Natural Resource Management	4,933	Energy Efficiency Improvement	4,865
Marine Ecology	4,845	Forestry Equipment	4,827
Carbon Markets	4,748	Climate Modeling	4,744
Net Ecosystem Exchange	4,465	Soil Contamination	4,293
Renewable Energy Markets	4,167	Aquatic Ecology	4,160
Exterior Insulation Finishing Systems	4,143	Green Bond	4,117
Light Rail Transit Systems	4,083	Climate Resilience	4,077
Solar Development	3,978	Carbon Capture And Storage	3,971
Sewage Sludge Treatment	3,958	Solar Collectors	3,939
Smart Meter Installation	3,918	Solar Products	3,903
Atmospheric Sciences	3,881	Powdered Activated Carbon Treatments	3,839
Terrestrial Ecology	3,797	Emissions Trading	3,776
Biorefinery	3,716	Ethanol Fuel	3,684
Solar Energy Systems Installation	3,524	Ecological Services	3,516
Paris Agreement	3,513	Electric Vehicle (EV) Installation	3,487
Carbon Offsets	3,459	Water Pollution	3,365
Hazardous Waste Disposal	3,337	Energy Analysis	3,320
Rainwater Harvesting	3,293	Organic Food	3,286
Hydrologic Modeling	3,256	Solar Roofs	3,241
Low Carbon Solutions	3,234	ISO 14064	3,224
Renewable Fuels	3,121	Biological Pest Controls	3,104
Wind Farm Development	2,880	Condensing Boiler	2,878
Coastal Engineering	2,825	E-Waste	2,825
Limnology	2,767	Industrial Wastewater Treatments	2,751
Invasive Species Management	2,701	Conservation Planning	2,681
LEED Accredited Professional (AP)	2,664	Integrated Assessment Modelling	2,619
Green Walls	2,485	Forest Protection	2,485
Water Filters	2,478	Professional Wetland Scientist	2,467
Forest Conservation	2,451	Environmental Remediation	2,428
Energy Efficiency Technologies	2,426	Water Conservation	2,389
Marine Conservation	2,381	Conservation Biology	2,315
Sulfur Hexafluoride	2,293	Ecological Restoration	2,280

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Table D.5: All green skills (main specification) (Continued)

Skill	Ad count	Skill	Ad count
Regenerative Agriculture	2,271	Plant Identification	2,261
Solar Radiation	2,224	Compressed Air Energy Storage	2,210
Boiling Water Reactors	2,195	Tree Surveying	2,192
Biomedical Waste	2,139	Photodetector	2,072
Bioplastic	2,001	Weather Stations	1,998
Energy Recovery Ventilation	1,991	Certified Landfill Manager	1,974
Storm Drains	1,944	Solar Thermal Systems	1,921
Agroforestry	1,920	Solar Sales	1,893
Circular Solutions	1,892	Marine Mammals	1,842
Coastal Management	1,790	Secchi Disk	1,781
Wildlife Ecology	1,721	Groundwater Remediation	1,699
Waste Characterization	1,686	IT Asset Disposition (ITAD)	1,678
United Nations Environment Programme Finance Initiative Treaties (UNEP-FI)	1,663	Vehicle Emissions Controls	1,651
Conservation Science	1,574	Vapor Barrier	1,570
Electrolysis Of Water	1,566	Wind Farm Construction	1,564
Building Performance Modeling And Simulations	1,546	Open Charge Point Protocols	1,543
Flood Controls	1,533	Fisheries Management	1,521
Solar Design	1,498	Wind Turbine Technology	1,496
Watershed Management	1,454	Forest Ecology	1,434
Nuclear Design	1,419	Crop Rotation	1,388
Liquid Hydrogen	1,378	Wind Farm Design	1,371
Community Ecology	1,325	Electric Vehicle Repair	1,319
Food Waste Management	1,317	Blower Doors	1,309
Emission Calculations	1,292	Chlorofluorocarbons (Freon)	1,287
Atmospheric Chemistry	1,285	Passive Solar Building Design	1,282
Climate Analysis	1,243	Fusion Power	1,228
Energy Efficiency Services	1,224	Ecosystem Management	1,220
Emission Standards	1,220	Atmospheric Physics	1,220
Aquatic Biology	1,168	Atmospheric Modeling	1,168
Air Sealing	1,162	Fuel Cell Vehicles	1,160
Solar Inverter	1,157	Sustainable Remediation	1,152
Resource Conservation And Recovery Act (RCRA)	1,138	Environmental Biotechnology	1,129
Nanofiltration	1,121	Leachate	1,120
Freshwater Ecology	1,109	Habitat Assessment	1,093
Flood Forecasting	1,083	Anemometers	1,067
Erosion Control	1,055	Certified Energy Plans Examiner	1,055
Materials Recovery Facility	1,029	Glaciology	1,029
Energy Demand Management	1,008	Evaporative Cooler	996
Phenology	992	Invasive Plants	987
Geothermal Energy	985	Thermal Energy Storage	967
Weather Satellites	965	Environmental Toxicology	958
Biofuel Production	952	Solar Photovoltaic Design	949
Surge Tank	939	Coastal Ecology	931
Municipal Waste Management	923	Water Reclamation	920
Plant Ecology	920	Certified Energy Manager	919
Urban Forestry	884	Emissions Inventory	864
Biopesticides	861	Forest Genetics	850
Chemical Ecology	847	Riparian Ecology	808
Water Quality Modeling	806	Emission Testing	792
Urban Ecology	788	Wildlife Habitats	783
Marine Habitats	782	Stack Emission Measurements	782
Vapor Recovery	779	Continuous Emissions Monitoring Systems	778
Insolation	750	Analysis Integration And Modeling Of The Earth System (AIMES)	733
Energy Efficient Lighting	732	Climate Information	711
Biomass Conversion	699	Forest Planning	687

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Table D.5: All green skills (main specification) (Continued)

Skill	Ad count	Skill	Ad count
Energy Star	685	Cycling Infrastructure	676
Environmental Mitigation	666	Heat Recovery Steam Generators	643
Urban Resilience	639	Energy Efficient Operations	625
Nickel Metal Hydride (NiMH Batteries)	617	Design For Environment (DfE)	613
Biodegradation	605	Spray Foam Insulation	602
Climate Change Programs	597	Weather Warning	593
Solid Waste Management	591	Climate Data Exchange (CDX)	587
EPA 608 Technician Certification	571	Habitat Conservation	568
Bioremediation	567	Waste Disposal Systems	566
Soil Health	558	Pipe Insulation	554
Smart Meter Installation Code of Practice (SMICoP)	549	Applied Ecology	526
Soil Biology	524	Ecological Engineering	523
Sustainable Landscaping	502	Advanced Distribution Automation	492
Solar Panel Assembly	474	Constructed Wetland	472
Energy Management Planning	464	Restoration Ecology	461
Climate Prediction	458	Polycrystalline Silicon	458
Wildlife Monitoring	444	Heat Pump System	438
Artificial Photosynthesis	421	Forest Restoration	419
Forest Mensuration	417	Certified Hazardous Materials Manager	410
Wetland Restoration	407	Evaporative Emission Control System	402
Membrane Electrode Assembly	395	Soil Ecology	394
Transportation Demand Management (TDM)	393	Ecosystem Ecology	391
Battery Cell Manufacturing	390	Solar Application	389
Biodiesel Production	384	Emission Reduction Projects	382
Commercial Solar Projects	380	Bus Rapid Transit	379
Hydrofluorocarbon	377	Fugitive Emissions	376
Storm Windows	368	Biological Oceanography	364
Activated Sludge Treatment	361	Ocean Biogeographic Information Systems	359
Emerging Contaminants	355	Wildlife Biology	355
Certified Energy Manager In Training	353	Heat Pump And Refrigeration Cycle	346
Brownfield Redevelopment	343	Vegetation Surveys	326
Electrocatalyst	326	Hazardous Material Containment And Control	323
Soil Microbiology	306	Wetland Ecology	306
Water Quality Studies	305	CFC Refrigeration Certification	301
Flywheel (Energy Storage)	296	Membrane Bioreactor	290
Hazardous Waste Operations And Emergency Response Standard (HAZWOPER)	286	Dendrology	280
Sustainable Gardening	280	Paleoclimatology	278
Solar Thermal Installation	276	Cadmium Telluride	273
Energy Efficiency Assessment	273	Thinning	269
Leachate Management	269	Solar Manufacturing	267
Tire Recycling	265	Harmful Algal Blooms	263
Coastal Development Hazards	257	LEED Green Associate	254
Land-Atmosphere Interactions	245	Low Carbon Development	244
Solar Lamps	243	Solar Cell Manufacturing	242
Electric Arc Furnace	241	Reverse Osmosis Plant	237
Ocean Quality Systems	234	Wastewater Distribution	228
Renewable Natural Gas	226	Renewable Energy Sales	223
Yaw Systems	222	Soft Engineering	220
Hydrograph	220	Solar Architecture	219
Forest Pathology	217	Sediment Controls	216
Timber Management	210	Refrigerant Reclamation	208
Wildfire Management	206	Flood Insurance	205
Ammoniacal Nitrogen	198	Coastal Science	198
Denitrification	192	Solar Consulting	190
Distributed Generation Certified Professional	188	Kyoto Protocol	187

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Table D.5: All green skills (main specification) (Continued)

Skill	Ad count	Skill	Ad count
Aerial Firefighting	179	Forest Entomology	175
Glass Insulation	175	Nuclear Plant Design	173
Stream Restoration	172	Adaptive Reuse	171
Water Treatments Operation	171	Solar Simulator	169
Fish Conservation	168	Ocean Acidification	163
Surface Energy Balance Algorithm For Land (SEBAL)	161	Wetland Management	152
Variable Air Volume	148	Wildfire Suppression	146
Microbial Fuel Cell	137	Energy Efficiency Analysis	137
Regenerative Design	137	Home Energy Assessment	136
ANSI/ANS Standards	135	Avian Ecology	132
Fuel Cell Design	126	Alternative Fuel Vehicles	124
Certified Arborist	121	API Oil-Water Separator	120
Emissions Controls	120	Integrated Coastal Zone Management	120
Pollution Control Systems	115	Data Center Infrastructure Efficiency	112
Wastewater Treatment Plant Design	111	Landfill Design	110
Geothermal Heating	109	Building Energy Modeling Professional Certification	107
General Circulation Models	106	Cooling Efficiency	105
Concentrated Solar Power	103	Wetland Conservation	95
Drip Irrigation	93	Clean Water Act	90
Electrocoagulation	90	Air-Sea Interaction	90
Waste Tracking System	88	Dissolved Air Flotation	88
Oil Skimmer	86	Grapple Truck	86
Wetland Assessment	85	Hydrogen Liquefaction	83
Vermicompost	83	Wetland Delineation	82
Low Impact Development	81	Heat Pump Specialist	79
IEC 61215	78	Drainage District	77
Hydrogen Purifier	76	Forest Technology	72
Transit-Oriented Development	72	UL 1741	64
Nuclear Procurement	63	Clean Development Mechanism	63
Detention Basin	62	Nitrate Reduction	61
Nuclear Reactor Core	58	Natural Resources Law	57
Wastewater Operator Certification	56	NABCEP Certified Energy Practitioner	55
HAZWOPER Certification	51	Leachate Collection And Removal System	49
Michigan Air Emissions Reporting Systems	48	Reductive Dechlorination	48
HVAC Automation Systems	46	Wetland Science	45
Integrated Gasification Combined Cycle	45	Landfill Gas Collection	45
Nuclear Core Design	42	IMI Level 3 Award In Electric/Hybrid Vehicle System Repair And Replacement	41
Certified Lighting Management Consultant	41	Nuclear Criticality Safety	41
Endangered Species Act	38	Water Erosion Prediction Project (WEPP) Model	34
Daylight Modeling	32	Emissions Analyzers	32
Residential Energy Efficiency	31	NATE Certified Ground Source Heat Pump Installer	31
Leadership in Energy and Environmental Design (LEED) Rating System	31	Stormwater Collection Systems	30
Certified Building Commissioning Professional	30	Aquatic Botany	28
Energy Efficiency Research	28	Bioindicator	27
Conservation Medicine	24	IEC 61730	24
Residential Energy Conservation	23	Catalytic CO2 Activation	23
SAE J1772	23	Water Resources Development Act	21
Fish And Wildlife Coordination Act	19	Natural Hazard Mitigation	19
Trickling Filter	18	Building Energy Codes	17
Hazardous Waste Manifests	17	Extended Aeration	16
Global Energy And Water Cycle Experimentation	15	Soil Vapor Extraction	15
Total Maximum Daily Load	15	Geothermal Gradient	14
Wetland Professional In Training	14	Universal Soil Loss Equations	13

Continued on next page

Table D.5: All green skills (main specification) (Continued)

Skill	Ad count	Skill	Ad count
Stormwater Monitoring	13	Comprehensive Environmental Response Compensation and Liability Act (CERCLA)	11
Soil Genesis	11	Firebreak	11
Renewable Portfolio Standard	10	EPA Type II Certification	9
Plasma Gasification	9	Inter-City Rail	9
Liquid Industrial Waste Service	9	EPA Type I Certification	7
Annual Energy Management Report	6	Certified Professional In Erosion And Sediment Control (CPESC)	6
Electric Vehicle Infrastructure Training Program (EVITP)	6	Floodplain	5
Marine Mammal Protection Act	5	IMI Level 2 Award In Electric/Hybrid Vehicle Routine Maintenance Activities	5
Habitat Conservation Plan	4	IMI Level 4 Award In The Diagnosis Testing And Repair Of Electric/Hybrid Vehicles And Components (VRQ)	4
Intended Nationally Determined Contributions	4	Wastewater Collection System Operation	4
Silvics	3	IEC 61646	3
Natural Channel Design	3	Compact Fluorescent Lamp	3
Action for Climate Empowerment (ACE)	3	Air Stripping	2
Watershed Improvement	2	PV Installation Professional	2
Threatened And Endangered Species Surveys	1	Certified Professional In Storm Water Quality (CPSWQ)	1
Service And Repair Of Electric And Hybrid Vehicles	1	Certified Forester	1
Associate Wildlife Biologist (AWB)	1	Carbon Dioxide Scrubber	1
Certified Energy Professional	1	Aerated Lagoon	1
National Green Infrastructure Certification Program	1		

Table D.6: All fully green occupations (main specification)

Occupation	Ad count
Recycling / Sanitation Worker	114,120
Solar Installer	75,003
Weatherization Installer	44,896
Alternative Energy Manager	31,008
Insulation Worker	24,724
Forest / Conservation Technician	24,460
Wind Turbine Technician	15,794
Energy Efficiency Specialist	15,735
Solar Sales Representative	15,197
Renewable Energy Engineer	13,442
Waste / Recycling Coordinator	13,262
Energy Efficiency Engineer	9,823
Fuel Cell Engineer	8,744
Solar Engineer	7,084
Wind Energy Engineer	6,746
Site Remediation Specialist / Manager	1,936
Landfill Gas Technician	618

E Wage premium regressions robustness and extensions

E.1 Baseline robustness

Table E.1: Low-carbon wage premium estimates

	(1)	(2)	(3)
Low-carbon job	0.091***	0.091***	0.067***
	(0.006)	(0.006)	(0.004)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28

Notes: The table reports OLS estimates of the association between low carbon job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Low-carbon job is a dummy equal to one if the job posting is classified as low carbon. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2: Green wage premium estimates, unweighted

	(1)	(2)	(3)
Green job	0.044***	0.045***	0.040***
	(0.004)	(0.004)	(0.002)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.23	0.24	0.38

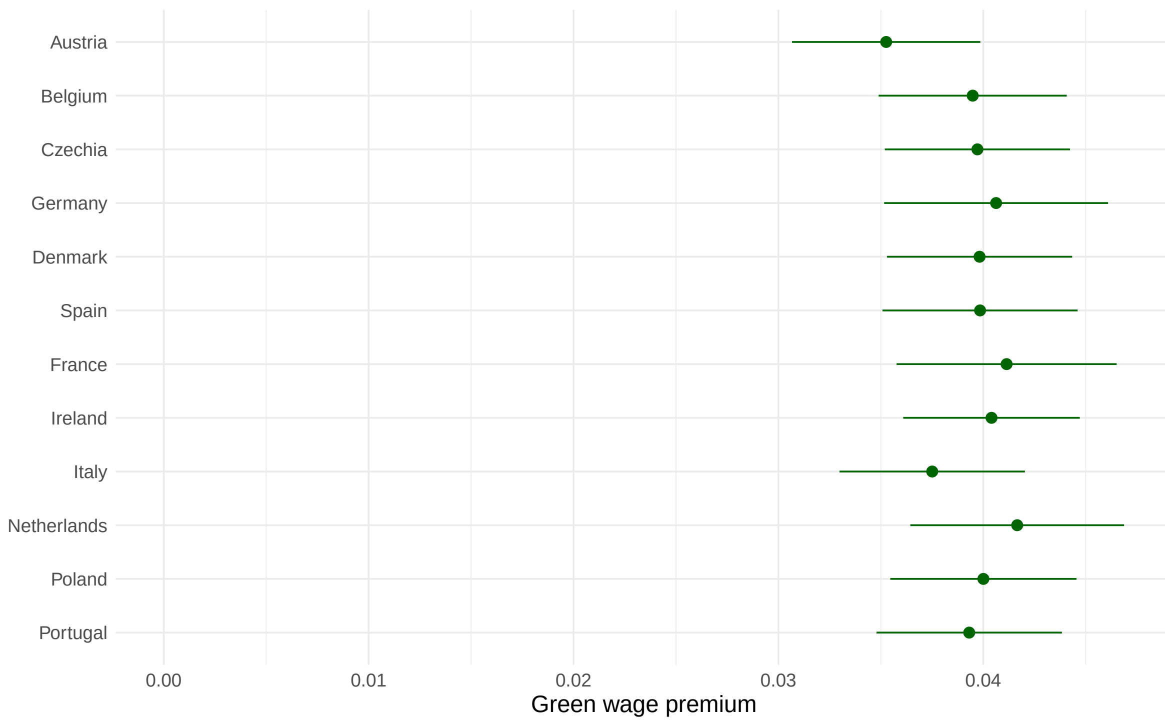
Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are unweighted. Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.3: Green wage premium estimates, clustered at NUTS2

	(1)	(2)	(3)
Green job	0.075***	0.077***	0.055***
	(0.005)	(0.005)	(0.004)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure E.1: Green wage premium estimates, excluding one country at the time



Notes: The figure reports leave-one-country-out estimates of the green wage premium at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Each point corresponds to the estimated coefficient on the green job indicator obtained by excluding the indicated country from the sample. The specification includes country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Horizontal bars denote 95% confidence intervals based on standard errors clustered at the NUTS2–ISCO2 level.

Table E.4: Green wage premium estimates, clustered at ISCO2

	(1)	(2)	(3)
Green job	0.075***	0.077***	0.055***
	(0.022)	(0.022)	(0.016)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.5: Green wage premium estimates, ISCO 3-digit by year fixed effects

	(1)	(2)	(3)	(4)
Green job	0.075***	0.077***	0.055***	0.056***
	(0.005)	(0.005)	(0.004)	(0.004)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes	Yes
ISCO (3-digits) FE	No	No	Yes	Yes
ISCO (3-digits) × Year FE	No	No	No	Yes
Part-time dummy	Yes	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) includes 3-digit ISCO occupation fixed effects. Column (4) further includes 3-digit ISCO occupation × year fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.6: Green wage premium estimates, restricting to sectoral availability

	(1)	(2)	(3)
Green job	0.092***	0.097***	0.079***
	(0.007)	(0.007)	(0.006)
Country × Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	5,818,367	5,818,367	5,818,367
R^2	0.11	0.13	0.26

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. The sample is restricted based on availability of the sector (NACE REV. 2) variable. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.2 Heterogeneity

Table E.7: Green wage premium estimates, effect by year

	(1)	(2)	(3)
Green job - 2018	0.050***	0.054***	0.067***
	(0.009)	(0.009)	(0.008)
Green job - 2019	0.089***	0.094***	0.098***
	(0.010)	(0.010)	(0.009)
Green job - 2020	0.073***	0.076***	0.062***
	(0.008)	(0.008)	(0.007)
Green job - 2021	0.046***	0.048***	0.016*
	(0.010)	(0.010)	(0.008)
Green job - 2022	0.097***	0.098***	0.059***
	(0.006)	(0.006)	(0.005)
Green job - 2023	0.075***	0.076***	0.054***
	(0.007)	(0.006)	(0.005)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.13	0.15	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level, allowing the effect to vary by year. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. The reported coefficients correspond to the marginal effect of a green job in each year, computed as the sum of the main green job coefficient and its interaction with the corresponding year indicator. All specifications include country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.8: Green wage premium estimates, effect by 1-digit sector

	(1)	(2)	(3)
Green job - Utilities	0.269***	0.289***	0.115***
	(0.032)	(0.042)	(0.026)
Green job - Services	0.087***	0.091***	0.085***
	(0.008)	(0.008)	(0.007)
Green job - Primary	-0.093**	-0.069**	-0.027
	(0.036)	(0.031)	(0.032)
Green job - Manufacturing	0.069***	0.066***	0.038***
	(0.012)	(0.012)	(0.011)
Green job - Construction	0.051***	0.050***	0.046***
	(0.014)	(0.014)	(0.010)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	5,818,367	5,818,367	5,818,367
R^2	0.11	0.13	0.26

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level, allowing the effect to vary 1-digit NACE REV. 2 sector. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. The reported coefficients correspond to the marginal effect of a green job in each sector, computed as the sum of the main green job coefficient and its interaction with the corresponding sector indicator. All specifications include country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.9: Green wage premium estimates, by 1-digit ISCO occupation

	(1)	(2)	(3)
Green job - ISCO 9 - Elementary occupations	0.042***	0.045***	0.029***
	(0.006)	(0.005)	(0.005)
Green job - ISCO 8 - Plant and machine operators, and assemblers	0.053***	0.053***	0.030***
	(0.008)	(0.006)	(0.006)
Green job - ISCO 7 - Craft and related trades workers	0.026***	0.026***	0.025***
	(0.007)	(0.006)	(0.006)
Green job - ISCO 6 - Skilled agricultural, forestry and fishery workers	0.007	0.014	0.018
	(0.012)	(0.012)	(0.013)
Green job - ISCO 5 - Service and sales workers	0.105***	0.111***	0.106***
	(0.010)	(0.009)	(0.009)
Green job - ISCO 4 - Clerical support workers	0.068***	0.069***	0.074***
	(0.011)	(0.010)	(0.009)
Green job - ISCO 3 - Technicians and associate professionals	0.081***	0.083***	0.067***
	(0.007)	(0.007)	(0.007)
Green job - ISCO 2 - Professionals	0.041***	0.039***	0.044***
	(0.008)	(0.008)	(0.009)
Green job - ISCO 1 - Managers	-0.007	-0.004	-0.012
	(0.013)	(0.012)	(0.012)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	20,767,568	20,767,568	20,767,568
R^2	0.24	0.25	0.28

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level, allowing the effect to vary 1-digit ISCO occupation. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. The reported coefficients correspond to the marginal effect of a green job in each ISCO (1-digit) occupation, computed as the sum of the main green job coefficient and its interaction with the corresponding ISCO (1-digit) indicator. All specifications include country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.10: Green wage premium estimates, by 1-digit ISCO occupation excluding sales workers (ISCO 52)

	(1)	(2)	(3)
Green job - ISCO 9 - Elementary occupations	0.044***	0.046***	0.028***
	(0.006)	(0.005)	(0.005)
Green job - ISCO 8 - Plant and machine operators, and assemblers	0.050***	0.051***	0.026***
	(0.008)	(0.006)	(0.006)
Green job - ISCO 7 - Craft and related trades workers	0.027***	0.027***	0.025***
	(0.006)	(0.006)	(0.006)
Green job - ISCO 6 - Skilled agricultural, forestry and fishery workers	0.001	0.010	0.011
	(0.012)	(0.012)	(0.013)
Green job - ISCO 5 - Service and sales workers	0.053***	0.061***	0.064***
	(0.011)	(0.013)	(0.009)
Green job - ISCO 4 - Clerical support workers	0.068***	0.069***	0.073***
	(0.011)	(0.010)	(0.009)
Green job - ISCO 3 - Technicians and associate professionals	0.082***	0.083***	0.068***
	(0.007)	(0.007)	(0.007)
Green job - ISCO 2 - Professionals	0.041***	0.039***	0.044***
	(0.008)	(0.008)	(0.009)
Green job - ISCO 1 - Managers	-0.007	-0.004	-0.012
	(0.013)	(0.012)	(0.012)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Observations	18,125,544	18,125,544	18,125,544
R^2	0.27	0.28	0.31

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level, allowing the effect to vary 1-digit ISCO occupation. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. The reported coefficients correspond to the marginal effect of a green job in each ISCO (1-digit) occupation, computed as the sum of the main green job coefficient and its interaction with the corresponding ISCO (1-digit) indicator. All specifications include country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. The sample excludes sales workers (ISCO 2-digit occupation 52). Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.3 Firm fixed effects and non-monetary attributes

Table E.11: Green wage premium estimates, clustered at firm level

	(1)	(2)	(3)
Green job	0.038***	0.038***	0.030***
	(0.007)	(0.006)	(0.006)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time dummy	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	15,742,224	15,742,224	15,742,224
R^2	0.53	0.53	0.56

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. All columns control for firm fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.12: Green wage premium estimates, excluding the top 10 advertising firms in each country

	(1)	(2)	(3)
Green job	0.037***	0.037***	0.029***
	(0.006)	(0.006)	(0.005)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	No	Yes	Yes
ISCO (3-digits) FE	No	No	Yes
Part-time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	10,766,769	10,766,769	10,766,769
R^2	0.58	0.58	0.61

* p ¡ 0.1, ** p ¡ 0.05, *** p ¡ 0.01

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The estimating set in this robustness excludes the top 10 firms posting the most ads in our dataset, which are the main human resource providers. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country × year and part-time fixed effects. Column (2) additionally controls for NUTS-2 region fixed effects. Column (3) further includes 3-digit ISCO occupation fixed effects. All columns control for firm fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.13: Low-carbon wage premium estimates, non-monetary job ad attributes and firm fixed effects

	(1)	(2)	(3)	(4)
Low-carbon job	0.074***	0.071***	0.037***	0.036***
	(0.005)	(0.005)	(0.003)	(0.003)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Non-monetary skills FE	No	Yes	No	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224
R^2	0.28	0.28	0.56	0.56

Notes: The table reports OLS estimates of the association between low carbon job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Low carbon job is a dummy equal to one if the job posting is classified as low carbon according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Column (2) additionally controls for non-monetary job attributes. Column (3) introduces firm fixed effects, restricting the sample to firms posting multiple vacancies. Column (4) combines firm fixed effects and non-monetary job attribute fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.14: Green wage premium estimates, controlling for non-monetary job ad attributes and firm fixed effects with narrow green skill definition

	(1)	(2)	(3)	(4)
Green job	0.082***	0.078***	0.035***	0.034***
	(0.006)	(0.006)	(0.004)	(0.004)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Non-monetary skills FE	No	Yes	No	Yes
Observations	15,748,601	15,748,601	15,748,601	15,748,601
R^2	0.28	0.28	0.56	0.56

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Column (2) additionally controls for non-monetary job attributes. Column (3) introduces firm fixed effects, restricting the sample to firms posting multiple vacancies. Column (4) combines firm fixed effects and non-monetary job attribute fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221,942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.15: Green wage premium estimates, controlling for non-monetary job ad attributes and firm fixed effects with broad green skills definition

	(1)	(2)	(3)	(4)
Green job	0.069***	0.065***	0.035***	0.035***
	(0.004)	(0.004)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Non-monetary skills FE	No	Yes	No	Yes
Observations	15,739,240	15,739,240	15,739,240	15,739,240
R^2	0.28	0.28	0.56	0.57

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Column (2) additionally controls for non-monetary job attributes. Column (3) introduces firm fixed effects, restricting the sample to firms posting multiple vacancies. Column (4) combines firm fixed effects and non-monetary job attribute fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221,942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.4 Returns to skills

Table E.16: Low-carbon wage premium estimates, controlling for skill types in job ad

	(1)	(2)	(3)	(4)	(5)	(6)
Low-carbon job	0.074***	0.071***	0.057***	0.037***	0.036***	0.029***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Non-monetary skills FE	No	Yes	Yes	No	Yes	Yes
Broad skills FE	No	No	Yes	No	No	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224	15,742,224	15,742,224
R^2	0.28	0.28	0.30	0.56	0.56	0.57

Notes: The table reports OLS estimates of the association between low carbon job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Low carbon job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Columns (2) and (3) add non-monetary job attributes fixed effects, while column (3) further introduces broad skill-type fixed effects. Columns (4)–(6) include firm fixed effects, restricting the sample to availability of firms' name information. Column (5) adds non-monetary job attribute fixed effects, and column (6) additionally controls for broad skill-type fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.17: Green wage premium estimates, controlling for skill types in job ad with narrow green skills definition

	(1)	(2)	(3)	(4)	(5)	(6)
Green job	0.082***	0.078***	0.064***	0.035***	0.034***	0.027***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Part-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Non-monetary skills FE	No	Yes	Yes	No	Yes	Yes
Broad skills FE	No	No	Yes	No	No	Yes
Observations	15,748,601	15,748,601	15,748,601	15,748,601	15,748,601	15,748,601
R^2	0.28	0.28	0.30	0.56	0.56	0.57

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Columns (2) and (3) add non-monetary job attributes fixed effects, while column (3) further introduces broad skill-type fixed effects. Columns (4)–(6) include firm fixed effects. Column (5) adds non-monetary job attribute fixed effects, and column (6) additionally controls for broad skill-type fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.18: Green wage premium estimates, controlling for skill types in job ad with broad green skills definition

	(1)	(2)	(3)	(4)	(5)	(6)
Green job	0.069***	0.065***	0.051***	0.035***	0.035***	0.028***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Part-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Non-monetary skills FE	No	Yes	Yes	No	Yes	Yes
Broad skills FE	No	No	Yes	No	No	Yes
Observations	15,739,240	15,739,240	15,739,240	15,739,240	15,739,240	15,739,240
R^2	0.28	0.28	0.30	0.56	0.57	0.57

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green according to our task-based taxonomy. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Columns (2) and (3) add non-monetary job attributes fixed effects, while column (3) further introduces broad skill-type fixed effects. Columns (4)–(6) include firm fixed effects. Column (5) adds non-monetary job attribute fixed effects, and column (6) additionally controls for broad skill-type fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.19: Returns to skills, green and non-green, with and without firm fixed effects

	Without Firm FE		With Firm FE	
	Green	Non-green	Green	Non-green
Soft skills	0.119***	-0.040***	0.079***	-0.036***
	(0.011)	(0.005)	(0.007)	(0.004)
Cooperation	0.008	0.045***	0.004	0.011***
	(0.010)	(0.005)	(0.007)	(0.002)
Purpose	0.005	-0.059***	0.037***	-0.036***
	(0.021)	(0.014)	(0.014)	(0.007)
Independence	0.019	0.078***	-0.006	0.053***
	(0.016)	(0.004)	(0.010)	(0.003)
Creativity	0.050***	0.062***	0.029***	0.032***
	(0.012)	(0.004)	(0.007)	(0.002)
Cognitive	0.043***	0.073***	0.019***	0.050***
	(0.015)	(0.004)	(0.006)	(0.003)
IT	0.019***	0.057***	0.012***	0.033***
	(0.007)	(0.003)	(0.004)	(0.001)
Management	0.039***	0.077***	0.018***	0.059***
	(0.006)	(0.003)	(0.004)	(0.002)
Social	0.090***	0.024***	0.053***	0.016***
	(0.009)	(0.003)	(0.005)	(0.002)
Technical	0.033***	0.082***	0.015***	0.048***
	(0.007)	(0.003)	(0.005)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224

Notes: The table reports OLS estimates of the association between skill requirements and log advertised salaries at the job-ad level, separately for green and non-green job postings. The dependent variable is the logarithm of the posted annual salary. Each coefficient measures the return to the corresponding skill category within green and non-green jobs, respectively. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.20: Returns to skills, low-carbon and non-low carbon, with and without firm fixed effects

	Without Firm FE		With Firm FE	
	Low Carbon	Non-low carbon	Low Carbon	Non-low carbon
Soft skills	0.144***	-0.039***	0.081***	-0.035***
	(0.013)	(0.005)	(0.009)	(0.004)
Cooperation	0.045***	0.045***	0.030***	0.010***
	(0.013)	(0.005)	(0.008)	(0.002)
Purpose	0.012	-0.059***	0.024	-0.035***
	(0.030)	(0.014)	(0.017)	(0.006)
Independence	0.018	0.078***	-0.006	0.053***
	(0.018)	(0.004)	(0.012)	(0.003)
Creativity	0.080***	0.063***	0.048***	0.032***
	(0.016)	(0.004)	(0.010)	(0.002)
Cognitive	0.027**	0.074***	0.031***	0.049***
	(0.011)	(0.004)	(0.009)	(0.003)
IT	0.056***	0.057***	0.022***	0.033***
	(0.009)	(0.003)	(0.005)	(0.001)
Management	0.046***	0.078***	0.024***	0.059***
	(0.010)	(0.003)	(0.005)	(0.002)
Social	0.108***	0.025***	0.049***	0.017***
	(0.010)	(0.003)	(0.006)	(0.002)
Technical	0.050***	0.082***	0.029***	0.048***
	(0.009)	(0.003)	(0.006)	(0.002)
Country × Year FE	Yes	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes	Yes
ISCO (3-digits) FE	Yes	Yes	Yes	Yes
Part-time dummy	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Observations	15,742,224	15,742,224	15,742,224	15,742,224

Notes: The table reports OLS estimates of the association between skill requirements and log advertised salaries at the job-ad level, separately for low carbon and non-low carbon job postings. The dependent variable is the logarithm of the posted annual salary. Each coefficient measures the return to the corresponding skill category within low carbon and non-lowcarbon jobs, respectively. All specifications include country × year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are reported in parentheses and are clustered at the NUTS2–ISCO2 level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.5 Oaxaca-Blinder decomposition

Table E.21: Oaxaca Blinder decomposition, full variables

	(1)		(2)	
	Coef.	(SE)	Coef.	(SE)
Green Job	0.0568***	(0.0041)	0.0235***	(0.0023)
Non-green Job	-0.0014	(0.0018)	-0.0006	(0.0011)
Difference	0.0582***	(0.0043)	0.0241***	(0.0025)
Endowments	0.0186***	(0.0011)	0.0063***	(0.0004)
Coefficients	0.0429***	(0.0042)	0.0190***	(0.0025)
Interaction	-0.0033***	(0.0011)	-0.0012***	(0.0003)
Endowments				
Creativity	0.0023***	(0.0003)	0.0006***	(0.0001)
Independence	0.0003***	(0.0000)	0.0000	(0.0000)
Purpose	0.0001**	(0.0000)	0.0000	(0.0000)
Cooperation	0.0002***	(0.0001)	0.0000***	(0.0000)
Soft	-0.0002***	(0.0001)	-0.0002***	(0.0001)
Technical	0.0036***	(0.0003)	0.0013***	(0.0001)
Social	0.0007***	(0.0001)	0.0002***	(0.0000)
Management	0.0058***	(0.0005)	0.0028***	(0.0002)
IT	0.0029***	(0.0003)	0.0008***	(0.0001)
Cognitive	0.0025***	(0.0003)	0.0008***	(0.0001)
Part time	0.0003***	(0.0001)	-0.0000	(0.0000)
Total	0.0186***	(0.0011)	0.0063***	(0.0004)
Coefficients				
Creativity	0.0000	(0.0000)	0.0000	(0.0000)
Independence	0.0000	(0.0000)	0.0000	(0.0000)
Purpose	-0.0000	(0.0000)	-0.0000	(0.0000)
Cooperation	0.0000	(0.0000)	0.0000	(0.0000)
Soft	-0.0000	(0.0000)	-0.0000	(0.0000)
Technical	0.0000	(0.0000)	0.0000	(0.0000)
Social	-0.0000	(0.0000)	-0.0000	(0.0000)
Management	0.0000	(0.0001)	0.0000	(0.0000)
IT	0.0000	(0.0000)	0.0000	(0.0000)
Cognitive	0.0000	(0.0000)	0.0000	(0.0000)
Part time	-0.0000	(0.0000)	0.0000	(0.0000)
Intercept	0.0428***	(0.0041)	0.0190***	(0.0025)
Total	0.0429***	(0.0042)	0.0190***	(0.0025)
Interaction				
Creativity	-0.0003	(0.0004)	-0.0000	(0.0001)
Independence	-0.0001*	(0.0001)	-0.0000	(0.0000)
Purpose	0.0001**	(0.0000)	0.0000	(0.0000)
Cooperation	-0.0002***	(0.0001)	-0.0001**	(0.0000)
Soft	0.0003***	(0.0001)	0.0004***	(0.0001)
Technical	-0.0007**	(0.0003)	-0.0004***	(0.0001)
Social	0.0010***	(0.0003)	0.0002***	(0.0001)
Management	-0.0015***	(0.0005)	-0.0004**	(0.0002)
IT	-0.0013***	(0.0003)	-0.0005***	(0.0001)
Cognitive	-0.0005	(0.0005)	-0.0003***	(0.0001)
Part time	0.0000	(0.0000)	-0.0000	(0.0000)
Total	-0.0033***	(0.0011)	-0.0012***	(0.0003)
Num. Obs.	15742224		15742224	
Country × Year FE	Yes		Yes	
NUTS 2 FE	Yes		Yes	
ISCO (3-digits) FE	Yes		Yes	
Firm FE	No		Yes	

Notes. The table presents a threefold Oaxaca–Blinder decomposition of the green wage premium. The outcome is log wages residualised from fixed effects regressions including country × year, NUTS (2-digit), ISCO (3-digit), and part-time fixed effects; column (2) additionally includes firm fixed effects. The decomposition separates the wage gap into endowments (characteristics), coefficients (returns), and interaction components. The reference group is non-green jobs. Estimates are weighted by LFS ISCO 3-digit employment levels (average 2018–2023). Standard errors are obtained from 200 cluster bootstrap replications at the NUTS (2-digit) × ISCO (2-digit) level. Number of unique firms: 221942. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

F Skill gap, additional material

F.1 Additional descriptive evidence

Table F.1: Definitions of non-monetary job characteristics

Non-monetary job characteristic	Lightcast skills
Cooperation	*Teamwork, Coaching, Cooperation, Team Oriented, Humility, Politeness, Sincerity, Social Intelligence, Community Leadership*
Creativity	*Innovation, Creativity, Imagination, Intellectual Curiosity, Creative Thinking, Visionary, Creative Strategies, Creative Entrepreneurship*
Managerial	*Planning, Leadership, Organizational Skills, Influencing Skills, Decision Making, Entrepreneurship, Strategic Planning, Supervision, Positive Management Leadership*
Purpose-oriented	*Strong Work Ethic, Honesty, Stewardship, Intercultural Competence, Personal Integrity, Cultural Responsiveness*
Soft skills	*Enthusiasm, Empathy, Trustworthiness, Curiosity, Friendliness, Positivity, Patience, Relationship Management, Tenacity, Courage, Diplomacy, Calmness Under Pressure, Compassion, Persistence, Optimism, Hospitality, Emotional Intelligence, Self-Control, Extroverted, Emotional Stability, Social Perceptiveness*
Work independently	*Self-Motivation, Time Management, Proactivity, Ability To Meet Deadlines, Results Focused, Entrepreneurship, Goal-Oriented, Self-Discipline, Self-Confidence, Independent Thinking, Smart Work*

Notes: We manually classified relevant skills from the Lightcast skill category "Physical and Inherent Abilities" into these five non-monetary job characteristics.

Table F.2: Top Lightcast skills by skill family

Skill family	Number of skills	Top 20 skills
Cognitive	165	*Research, Statistics, Problem Solving, Troubleshooting (Problem Solving), Analytical Skills, Analytical Thinking, Research And Development, Market Research, Mathematics, Sampling (Statistics), Critical Thinking, Eight Disciplines Problem Solving (8D), Clinical Research, Analytical Chemistry, Analytical Techniques, Postdoctoral Research, Medical Research, Research Papers, Research Experiences, Applied Research*
IT	5008	*Personal Computers, JavaScript (Programming Language), Smartphone Operation, Computer Science, C (Programming Language), Agile Methodology, Calculators, Java Platform Micro Edition (J2ME), SQL (Programming Language), Digitization, Java (Programming Language), Automation, Scrum (Software Development), Linux, Software Development, Python (Programming Language), Information Systems, Application Programming Interface (API), Site Maps, C# (Programming Language)*
Management	848	*Management, Leadership, People Management, Project Management, Human Resource Management, Inventory Management, Office Management, Quality Management, Facility Management, Contract Management, Management Consulting, Materials Management, Product Management, Risk Management, Executive Leadership, Order Management, Staff Management, Project Management Institute (PMI) Methodology, Relationship Management, Stress Management*
Social	178	*Communication, Presentations, Teamwork, Negotiation, Information And Communications Technology, Telecommunications, Interpersonal Communications, Global System For Mobile Communications, Persuasive Communication, Marketing Communications, Verbal Communication Skills, Price Negotiation, Communication Strategies, Online Communication, Collaboration, Food Plating And Presentation, Corporate Communications, Effective Communication, TeleCommunications Engineering, Business Presentations*
Technical	236	*Construction, Mechanical Engineering, Mechanics, Technical Support, Building Services Engineering, Technical Training, Technical Acumen, Technical Documentation, Technical Drawing, Engineering Drawings, Technical Assistance, Building Information Modeling, Engineering Documentation, Technical Records, Engineering Plans And Specifications, Medical Response Technician, Certified Hemodialysis Technologist/Technician (CHT), Professional Technical Training, Technology Scouting, Construction Management*

Notes: This table lists the total number of Lightcast skills included in each of the five broad skill families, as well as the top 20 of these skills when ranked by the total number of ads within our wage regression sub-sample that require the skill.

Table F.3: Unconditional green skill gap between green and non-green jobs, by 1-digit ISCO occupation

	Cognitive		IT		Management		Social		Technical	
	1	2+	1	2+	1	2+	1	2+	1	2+
1 - Managers										
Not green	7.2%	0.8%	18.9%	10.6%	28.9%	20.6%	22.5%	5.4%	10.6%	3.0%
Green	10.0%	1.2%	22.4%	13.9%	29.1%	23.3%	23.8%	6.7%	16.2%	5.8%
2 - Professionals										
Not green	7.2%	0.9%	16.0%	19.4%	22.5%	8.4%	16.1%	3.3%	8.6%	2.3%
Green	13.3%	2.4%	20.9%	27.1%	25.8%	15.4%	21.6%	5.7%	16.3%	6.3%
3 - Technicians and associate professionals										
Not green	5.4%	0.4%	18.4%	6.6%	22.4%	9.1%	17.6%	3.4%	8.3%	1.8%
Green	8.0%	1.1%	22.8%	10.0%	23.4%	11.5%	18.1%	3.8%	14.1%	4.0%
4 - Clerical support workers										
Not green	4.7%	0.7%	21.6%	7.3%	17.5%	6.6%	14.7%	2.3%	3.4%	0.4%
Green	10.1%	2.6%	22.6%	15.0%	20.7%	10.6%	19.0%	4.0%	7.5%	1.3%
5 - Service and sales workers										
Not green	4.7%	0.2%	13.2%	6.9%	17.9%	4.5%	11.6%	2.4%	4.3%	0.5%
Green	14.1%	0.8%	14.6%	18.7%	26.5%	9.5%	15.2%	4.9%	13.0%	2.4%
6 - Skilled agricultural, forestry and fishery workers										
Not green	2.2%	0.0%	10.4%	2.3%	8.9%	1.6%	6.5%	0.7%	6.0%	0.6%
Green	7.2%	0.2%	9.0%	1.6%	11.6%	2.3%	3.7%	0.5%	4.1%	0.8%
7 - Craft and related trades workers										
Not green	3.3%	0.1%	14.7%	3.8%	11.5%	1.5%	6.7%	0.7%	10.7%	2.3%
Green	3.7%	0.3%	17.6%	5.7%	14.1%	2.8%	8.9%	1.2%	14.5%	3.2%
8 - Plant and machine operators, and assemblers										
Not green	1.7%	0.1%	17.6%	3.7%	11.6%	1.2%	5.1%	0.4%	5.7%	1.0%
Green	2.0%	0.2%	18.4%	5.7%	15.7%	2.5%	5.9%	0.5%	5.7%	1.1%
9 - Elementary occupations										
Not green	1.7%	0.1%	15.1%	3.4%	13.5%	1.8%	6.9%	0.6%	4.8%	0.8%
Green	2.6%	0.3%	16.2%	4.8%	18.1%	3.6%	8.7%	0.8%	7.4%	1.9%

Notes: Each value represents the share of ads for a given 1-digit ISCO occupation and category (green and not green) containing exactly one (1) or two or more (2+) skills pertaining to the broad skill family in the column header.

F.2 Decomposing the green skill gap

We closely follow the simple decomposition of the green skill gap proposed by Saussay et al., 2026. Let's define the share of job ads that contains skill s within 3-digit ISCO occupation k and job type i - either green ($i = g$) or non-green ads $i = ng$ - as $f^i_{sk} = \frac{n^i_{sk}}{n^i_k}$, we define the green skill gap for skill group s as:

$$f^g_s - f^{ng}_s = \sum_k \omega^g_k \omega_k \times (f^g_{sk} - f^{ng}_s), \tag{6}$$

where f^{ng}_s is the simple average share of job ads mentioning skill s across all occupations, ω^g_k is the share of green jobs in total jobs for occupation k and ω_k is the employment share of occupation k, accounting for the size of the occupation.[33]

This measure of the skill gap can bedecomposed into a within and between component as follows:

$$f^g_s - f^{ng}_s = \sum_k \omega^g_k \omega_k \times [(f^g_{sk} - f^{ng}_{sk}) + (f^{ng}_{sk} - f^{ng}_s)]. \tag{7}$$

The second term in the square bracket is the between-occupation component of the skill gap - that is, the extent to which the share of green jobs (ω^g_k) correlates with the difference in skill use across occupational groups. The first element in the square bracket is the within-occupation skill gap - that is, the difference in skill intensity between green and non-green jobs within the same occupational group. This component is unobservable in occupation-level datasets and can be measured thanks to the high granularity of the OJV data.

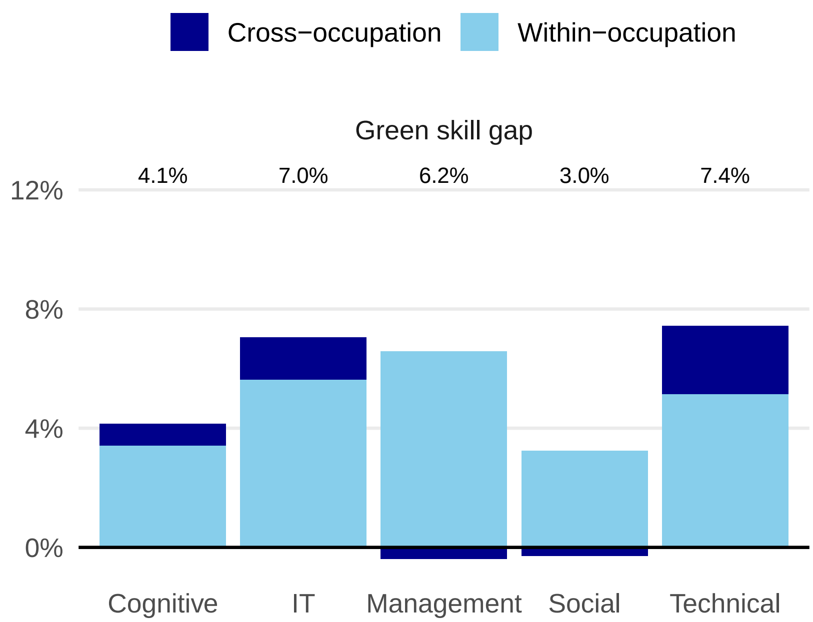
[33]For comparability, both measures are renormalized such that $\sum_k \omega^g_k \times \omega_k = 1$. This ensures that $f^g_s - f^{ng}_s$ can be interpreted as the average skill gaps across occupations at 3-digits.

Table F.4: Within- vs cross- occupation green skill gap

	Green share × Job ads share
Cognitive	**4.15%**
Within-occupation	3.43%
Cross-occupation	0.72%
IT	**7.05%**
Within-occupation	5.63%
Cross-occupation	1.41%
Management	**6.19%**
Within-occupation	6.58%
Cross-occupation	-0.39%
Social	**2.95%**
Within-occupation	3.25%
Cross-occupation	-0.29%
Technical	**7.44%**
Within-occupation	5.15%
Cross-occupation	2.28%

Notes: This figure shows average within- and between-occupation skill gaps across 3-digit ISCO occupations for the five major skill categories. These are calculated using the number of ads per 3-digit ISCO occupation in the Lightcast data as weights. Skill gaps are reported in percentage points, multiplying the difference in the shares by 100 for readability. Calculated from the sample of ads used in the wage regressions.

Figure F.1: Within- vs cross- occupation green skill gap



Notes: This figure shows average within- and between-occupation skill gaps across 3-digit ISCO occupations for the five major skill categories. These are calculated using the number of ads per 3-digit ISCO occupation in the Lightcast data as weights. Overall skill gaps (within + cross occupation skill gaps) are reported in the annotations above the bars. Calculated from the sample of ads used in the wage regressions.

F.3 Skill gap regressions robustness

Table F.5: Extensive margin green skill gap between green and non-green jobs, unweighted

	(1)	(2)	(3)
Panel A: Broad skills			
Green job - Cognitive	0.030***	0.027***	0.016***
	(0.002)	(0.002)	(0.001)
Green job - IT	0.071***	0.055***	0.033***
	(0.004)	(0.003)	(0.002)
Green job - Management	0.063***	0.071***	0.046***
	(0.004)	(0.003)	(0.002)
Green job - Social	0.029***	0.034***	0.017***
	(0.003)	(0.002)	(0.002)
Green job - Technical	0.062***	0.042***	0.030***
	(0.003)	(0.003)	(0.003)
Panel B: Non-monetary job attributes			
Green job - Cooperation	0.004***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)
Green job - Creativity	0.029***	0.031***	0.018***
	(0.002)	(0.002)	(0.001)
Green job - Independence	0.007***	0.008***	0.003**
	(0.002)	(0.002)	(0.002)
Green job - Purpose	-0.001**	-0.000	-0.001
	(0.000)	(0.000)	(0.000)
Green job - Soft skills	-0.000	0.009***	0.007***
	(0.002)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes
ISCO (3-digits) FE	No	Yes	Yes
Part-time FE	Yes	Yes	Yes
Firm FE	No	No	Yes
Observations	15,742,224	15,742,224	15,742,224
R^2	0.05	0.07	0.23

Notes: This table presents coefficient estimates from a series of job-level regressions. The dependent variable in each regression is a dummy variable indicating that a job requires at least one skill from the specified broad skill family or non-monetary job attribute category, and the explanatory variable is a dummy variable indicating the job is green. All regressions are estimated using the OLS estimator. Standard errors are clustered by ISCO 2-digit occupation by NUTS 2 region. Number of unique firms: 221942.
* = 0.1, ** = 0.05, *** = 0.01.

Table F.6: Extensive margin skill gap between low-carbon and non-low-carbon jobs

	(1)	(2)	(3)
Panel A: Broad skills			
Low-carbon job - Cognitive	0.027***	0.023***	0.018***
	(0.002)	(0.002)	(0.002)
Low-carbon job - IT	0.080***	0.057***	0.035***
	(0.006)	(0.005)	(0.004)
Low-carbon job - Management	0.044***	0.057***	0.052***
	(0.006)	(0.005)	(0.005)
Low-carbon job - Social	0.028***	0.032***	0.026***
	(0.004)	(0.004)	(0.002)
Low-carbon job - Technical	0.075***	0.057***	0.043***
	(0.004)	(0.003)	(0.003)
Panel B: Non-monetary job attributes			
Low-carbon job - Cooperation	0.002	0.003**	0.003***
	(0.001)	(0.001)	(0.001)
Low-carbon job - Creativity	0.025***	0.025***	0.017***
	(0.003)	(0.002)	(0.002)
Low-carbon job - Independence	0.003***	0.003***	0.001
	(0.001)	(0.001)	(0.001)
Low-carbon job - Purpose	-0.002***	-0.001***	-0.001
	(0.001)	(0.001)	(0.001)
Low-carbon job - Soft skills	-0.007***	0.000	0.006***
	(0.002)	(0.002)	(0.002)
Country × Year FE	Yes	Yes	Yes
NUTS (2-digits) FE	Yes	Yes	Yes
ISCO (3-digits) FE	No	Yes	Yes
Part-time FE	Yes	Yes	Yes
Firm FE	No	No	Yes
Observations	15,742,224	15,742,224	15,742,224
R^2	0.02	0.04	0.17

Notes: This table presents coefficient estimates from a series of job-level regressions. The dependent variable in each regression is a dummy variable indicating that a job requires at least one skill from the specified broad skill family or non-monetary job attribute category, and the explanatory variable is a dummy variable indicating the job is low carbon. All regressions are estimated using the OLS estimator. Standard errors are clustered by ISCO 2-digit occupation by NUTS 2 region. Estimates are weighted by LFS ISCO 3-digit employment levels (avg. 2018-2023). Number of unique firms: 221942.
* = 0.1, ** = 0.05, *** = 0.01.