



Jobs and Skills in the Green Transition: Local Multipliers and Returns to Green Tasks in Europe

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

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Abstract

When structural transformation generates demand for new tasks, the wage premium signals the return to acquiring the corresponding skills. We ask whether such incentives arise for green tasks, using online job vacancy data for European Union countries over 2018 to 2023 and a large language model classifier of green skill requirements. Green jobs command a premium of 5.5 percent over comparable postings within the same occupation. Firm fixed effects absorb roughly one half, consistent with firm rents, and skill complexity a further one tenth, leaving a residual return to green tasks of approximately 2 percent. Nonmonetary attributes matter little.

Keywords: Green wage premium, Skill gaps, Green tasks, LLM.

JEL: J24, J6, F64.

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

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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. Any structural transformation- whether driven by trade, technology, or policy - increases the demand for emerging tasks that complement new technologies, sectors or occupations (Autor et al., 2003; Lin, 2011). In competitive labour markets, emerging tasks are rewarded proportionally to their marginal contribution to output, which is expected to be higher than the marginal contribution of existing tasks as new technologies are more efficient than old ones (Acemoglu & Restrepo, 2019; Autor & Handel, 2013). In practice, however, returns to emerging tasks may be observationally different than their marginal productivity reflecting correlated characteristics of the jobs, firms, or workers involved. For instance, the endogenous sorting of workers with higher (resp. lower) skills into new roles increases (resp. decreases) the marginal value of emerging tasks for reasons unrelated to the intrinsic contribution of such tasks. Disentangling the various components of returns to emerging tasks is essential for understanding how labour markets adjust to structural change.

We study this question in the context of the green transition - where policy support and technological improvements increased rapidly the demand of green tasks. Improvements in the measurement of green activities and jobs make it possible to advance our understanding of the “green wage premium” - the pay differential between green and non-green jobs. A growing literature estimates a premium ranging from 4% to 10% 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). 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 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 can actually be attributed to higher marginal productivity of workers in green tasks, 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 greenness 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 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

¹Popp 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.

²Godøy 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.

³Cross-occupation comparisons faces several limitations. Notably, 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).

⁴Using 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.

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, i.e. the average marginal productivity of workers in such tasks.

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 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 main results on the green wage premium. Section 5 analyses 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; D. J. 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* skills⁵ 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

⁵Skills 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*.

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 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

⁶With 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.

green skill candidates and 54 green occupation candidates per model⁷.

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 models⁸ 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 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

⁷Green 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.

⁸These 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.

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 <i>at least half</i> 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 of the green wage premium 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 the wage 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).

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 provide an extensive analysis of the representativeness of the Lightcast data (both for the full and the wage sample) by comparing it to Labour Force Survey (LFS) data¹¹ in Appendix A. As expected, the Lightcast data over-represent some groups, for example, Germany, France and the Netherlands and high-

⁹See Table A.1 for missing value shares for the key variables in the wage sample.

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

¹¹EU 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.

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. Unsurprisingly, restricting the analysis to the wage sample does not improve the representativeness of Lightcast data with respect to LFS data across countries or occupations (See in particular Tables A.3 and A.5). To mitigate 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.¹² 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.¹³ 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 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

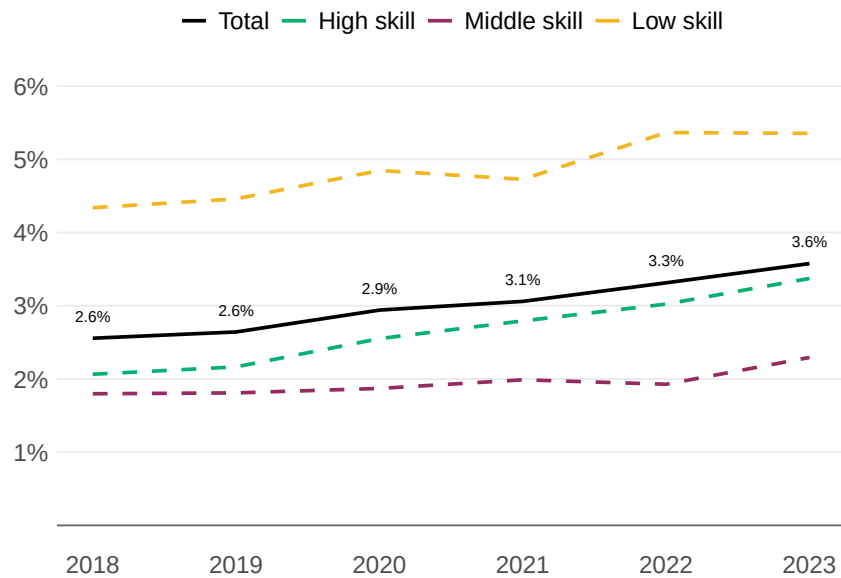
¹²Table C.3 shows that the green job share is very similar in the wage sample.

¹³These 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.

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

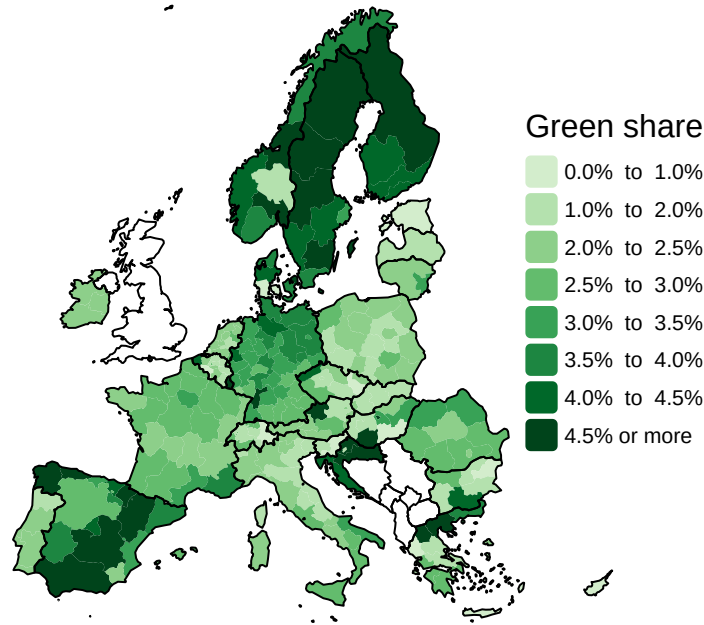


Notes. This figure includes EU27 countries plus Norway and Switzerland, and shows green job shares calculated using country-specific ISCO 3-digit occupation employment as weights. The annotations indicate aggregate green job shares (i.e. for all skill levels together). High skill covers ISCO 1-digit 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.¹⁴ 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.¹⁵ 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 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.¹⁶

¹⁴Low carbon job shares by sector, shown in Appendix Figure C.4, display qualitatively similar patterns.

¹⁵Appendix 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.

¹⁶These spatial patterns are broadly similar for low-carbon job shares (see Appendix Figure C.7), though overall shares tend to be lower.

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)¹⁷ and Lightcast’s experimental green skill classification.¹⁸ 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 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.

¹⁷European 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”.

¹⁸This 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).

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:

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

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; D. J. 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 unob-

served, skills into jobs with different task content (Autor & Handel, 2013; De La Rica et al., 2020; Gathmann & Schönberg, 2010; Hurst et al., 2024).¹⁹ 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:²⁰

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

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

¹⁹For 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.

²⁰Typically, 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).

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*** (0.005)	0.077*** (0.005)	0.055*** (0.004)
Country $\times$ 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 $\times$ 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%).²¹ 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.

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

²¹About 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.

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).²² 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 excluding large firms in top percentile of the job posting distribution that include also human resource providers (Appendix Table E.11), and limiting the analysis to low-carbon jobs (Table E.12). Importantly, the results are also qualitatively robust to both stricter and broader definitions of green skills (Tables E.13 and E.14).

Finally, in Table E.15, we allow the returns to green tasks to differ for green jobs whose underlying tasks have grown fastest in demand, by adding an indicator for jobs containing at least one fast-growing green task on top of the green job dummy.²³ The coefficient on fast-growing captures the premium these jobs command over and above other green jobs. Without firm fixed effects, this additional premium is large: fast-growing green jobs pay around 8 percentage points more than other green jobs (columns 1-2), bringing their total premium relative to non-green jobs to roughly 13%. Once firm fixed effects are introduced, however, the additional premium falls sharply to about

²²See 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.

²³To identify fast-growing green jobs, we use OJV data for the US, which span a much longer period (2010-2023), proceeding in two steps. First, we define a fast-growing green task as one that: i. is green according to our taxonomy; ii. increases its percentile in the frequency distribution by more than 25 percentiles between 2010-2012 and 2022-2023; iii. lies above the median of the 2022-2023 distribution. Fast-growing green tasks represent approximately 12% of green tasks and are predominantly low-carbon. Second and consistently with the rest of the paper, we define a fast-growing green job as a job containing at least one task that is green and fast-growing.

1.5 percentage points, and becomes imprecisely estimated ($p = 0.14$ in column 4). Firm fixed effects thus absorb the extra return to fast-growing green tasks, indicating that the higher pay associated with fast-growing green tasks is predominantly a firm-level phenomenon: higher-paying firms are also those that adopt and advertise fast-growing green tasks earliest. A small task-specific component nonetheless remains directionally positive if imprecise within firms and occupations, consistent with the returns-to-new-work literature (e.g. D. Deming & Noray, 2020).

Overall, Table 3 strengthens both the interpretation of our results and 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, especially for fast-growing green tasks. While firm rents are the main source of bias in previous estimates of the green wage premium (Bone et al., 2025; Kuai et al., 2025; Vona et al., 2019), they do not fully absorb the returns to green tasks that becomes smaller but remains highly statistically significant. This suggests that inferring the green wage premium from firm-level greenness (e.g. Godøy & Isaksen, 2025; Krueger et al., 2023) conflate firm rents with the task-specific return, missing the latter.

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

	(1)	(2)	(3)	(4)
Green job	0.059*** (0.004)	0.055*** (0.004)	0.030*** (0.006)	0.029*** (0.006)
Country $\times$ 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	15,742,224	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 $\times$ 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 firm 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.²⁴ These groups account for the main general skills that are rewarded in labour markets (see e.g. Altonji et al., 2012; D. J. 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.

In line with the task-based labour literature (Autor & Handel, 2013; Spitz-Oener, 2006), these

²⁴See Table F.2 in the Appendix for lists of the top 20 skills belonging to each family.

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.

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 component and a between-occupation component at 3-digit ISCO level (details are provided in Appendix F.3). Appendix Table F.8 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.²⁵

²⁵Regressions 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.

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.²⁶

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 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; D. J. 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.

²⁶In the Appendix, we show that unweighted estimates deliver similar results (Table F.9. Low-carbon ads also display similar patterns (Table F.10).

Table 5: Conditional green skill gap: extensive margin estimates

	(1)	(2)	(3)
Panel A: Broad skills			
Green job - Cognitive	0.038*** (0.004)	0.035*** (0.004)	0.021*** (0.002)
Green job - IT	0.076*** (0.005)	0.052*** (0.004)	0.030*** (0.003)
Green job - Management	0.071*** (0.006)	0.077*** (0.004)	0.059*** (0.004)
Green job - Social	0.029*** (0.003)	0.031*** (0.002)	0.016*** (0.002)
Green job - Technical	0.063*** (0.003)	0.044*** (0.003)	0.033*** (0.002)
Panel B: Non-monetary job attributes			
Green job - Cooperation	0.005*** (0.001)	0.005*** (0.001)	0.004*** (0.001)
Green job - Creativity	0.039*** (0.004)	0.039*** (0.004)	0.022*** (0.002)
Green job - Independence	0.004*** (0.001)	0.004*** (0.001)	0.000 (0.001)
Green job - Purpose	-0.002*** (0.000)	-0.001*** (0.000)	-0.000 (0.000)
Green job - Soft skills	-0.002 (0.002)	0.005*** (0.002)	0.008*** (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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.²⁷

²⁷Roughly the same proportions apply to low-carbon jobs, see Appendix Table F.4. Results are also very robust to the use of a broader (Table F.6) or more stringent definition of green job (Table F.5).

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*** (0.004)	0.055*** (0.004)	0.041*** (0.004)	0.030*** (0.006)	0.029*** (0.006)	0.022*** (0.006)
Country $\times$ 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	15,742,224	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 $\times$ 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 in columns (1), (2) and (3), and at the firm level in columns (4), (5), (6). Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

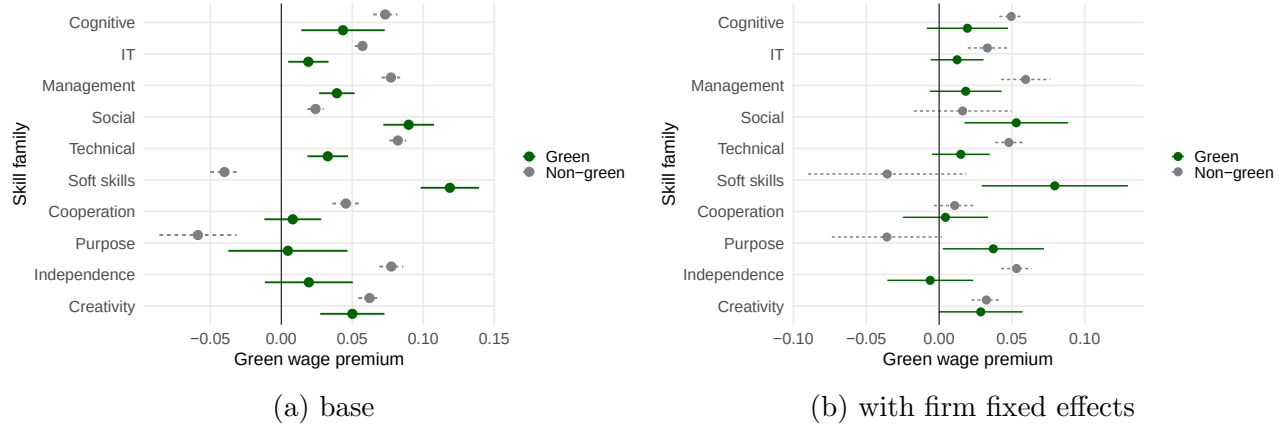
We next ask whether the relevant general skills are simply more prevalent in green jobs, or whether they also earn different returns in green and non-green vacancies. To do so we augment the main specifications with interaction terms between the green job dummy and each skill family dummy, included one at a time. Figure 3 panel (a) reports the corresponding coefficients, and Appendix Table F.7 provides the point estimates.

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 F.7). 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.²⁸

Adding firm fixed effects in Figure 3 panel (b) (see also Table F.7) confirms the same broad pattern, while also showing that firm rents account for part of the returns to general skills in both

²⁸For the low-carbon counterpart, results are again similar. See Appendix Table E.16.

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



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 $\times$ 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. Standard errors are clustered at the NUTS2–ISCO2 level in sub-figure (a) and at the firm level in sub-figure (b). The vertical line indicates zero. Number of unique firms: 221942.

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 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.²⁹ For each variable $v \in \{w, s_1, \dots, s_K\}$ we estimate:

²⁹The 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.

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

where $\mathbf{d}_{it}$ collects the fixed effects and $\tilde{v}_{it}$ is the residual net of all controls.³⁰ 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 $\tilde{\mathbf{s}}_i = (\tilde{s}_{1i}, \dots, \tilde{s}_{Ki})^\top$ for green ($h = g$) and non-green ($h = ng$) vacancies:

$$\tilde{w}_i = \tilde{\mathbf{x}}_i^\top \boldsymbol{\beta}^h + \alpha^h + \varepsilon_i^h, \quad h \in \{g, ng\}, \quad (4)$$

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

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

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 $\times$ ISCO-2 level. This propagates uncertainty from both the residualization stage and the group-specific wage regressions into the final decomposition estimates.

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

³⁰The fixed effects included are: NUTS-2, country-by-year, ISCO 3-digit and, depending on the specification, firm.

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 $\times$ 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 $\times$ 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) $\times$ ISCO (2-digit) level. Number of unique firms: 221,942. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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.³¹

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

³¹Fortin 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.

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.17).

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%),³² 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.

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

³²Using 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 in 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.

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 that captures the additional productivity of workers in these tasks, 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. On the one hand, 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. On the other hand, studies that do not allow for a fine-grained breakdown of green and non-green tasks within the firm miss the task-specific component of the green premium.

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. This pattern is substantially the same if we restrict this representativeness to the countries (and ads) that enter the wage premium estimating sample (Table A.3).

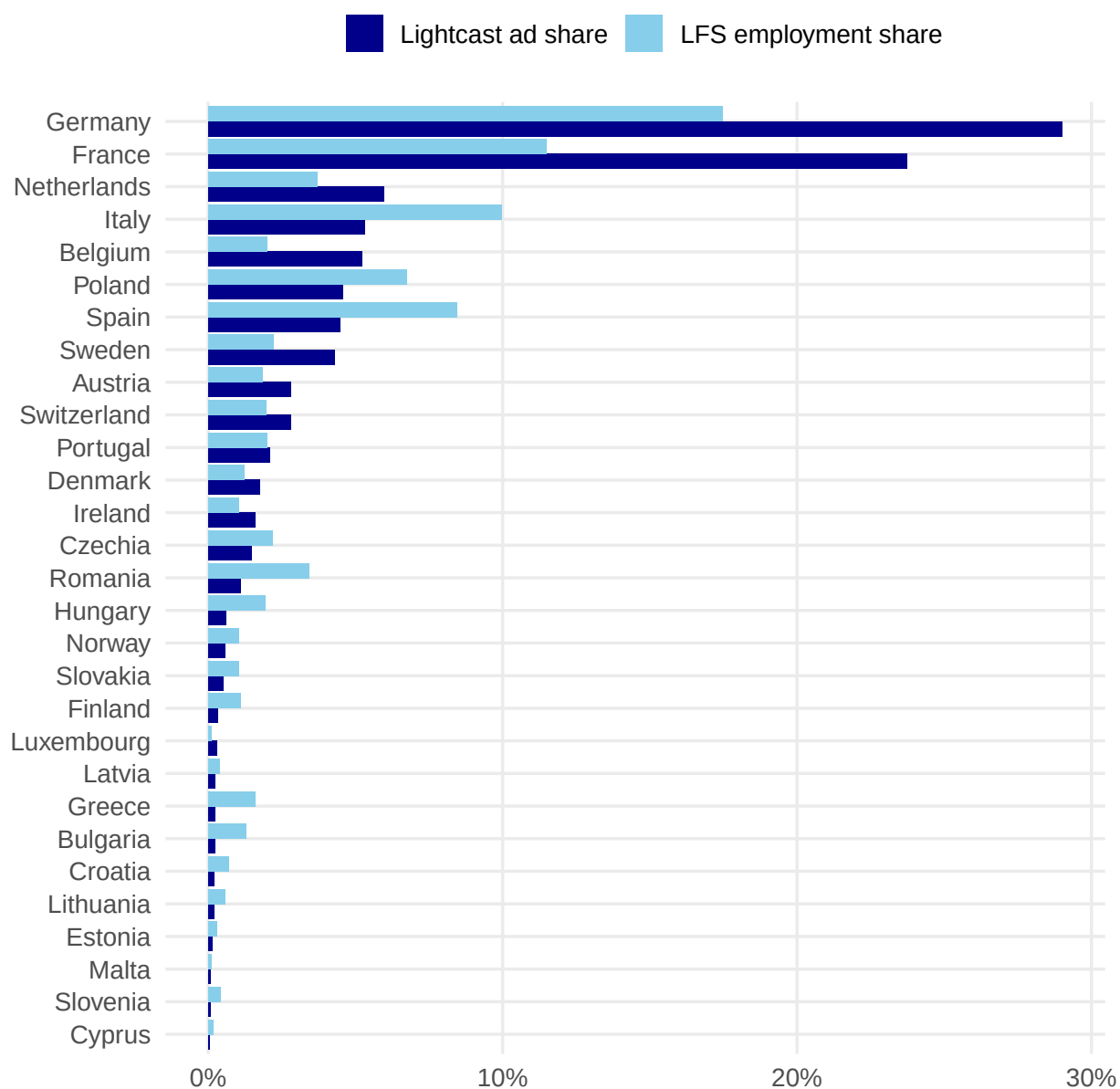
A similar pattern emerges across occupations. Table A.4 and Figure A.2 compare 2-digit ISCO shares in the Lightcast and LFS data. Occupations such as sales workers (ISCO 52), business administration professionals and associate professionals (ISCO 24 and 33), and ICT professionals (ISCO 25) are over-represented 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. Again, this pattern is substantially the same if we restrict this representativeness to the countries (and ads) that enter the wage premium estimating sample (Table A.5).

Table A.1: Missing value shares for key variables

	Total ads	Share missing				
		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 includes 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: Country shares and ad counts: Lightcast vs. Labour Force Surveys. Wage sample

Country	Ad count	Unweighted ad share	LFS employment share
France	6,710,070	32.31%	16.29%
Germany	5,585,592	26.9%	25.08%
Netherlands	3,460,140	16.66%	5.72%
Austria	2,069,217	9.96%	2.61%
Spain	1,025,358	4.94%	12.61%
Ireland	579,076	2.79%	1.55%
Poland	364,370	1.75%	10.67%
Italy	315,408	1.52%	13.86%
Belgium	304,390	1.47%	2.93%
Czechia	223,292	1.08%	3.45%
Portugal	98,065	0.47%	3.07%
Denmark	32,590	0.16%	2.14%

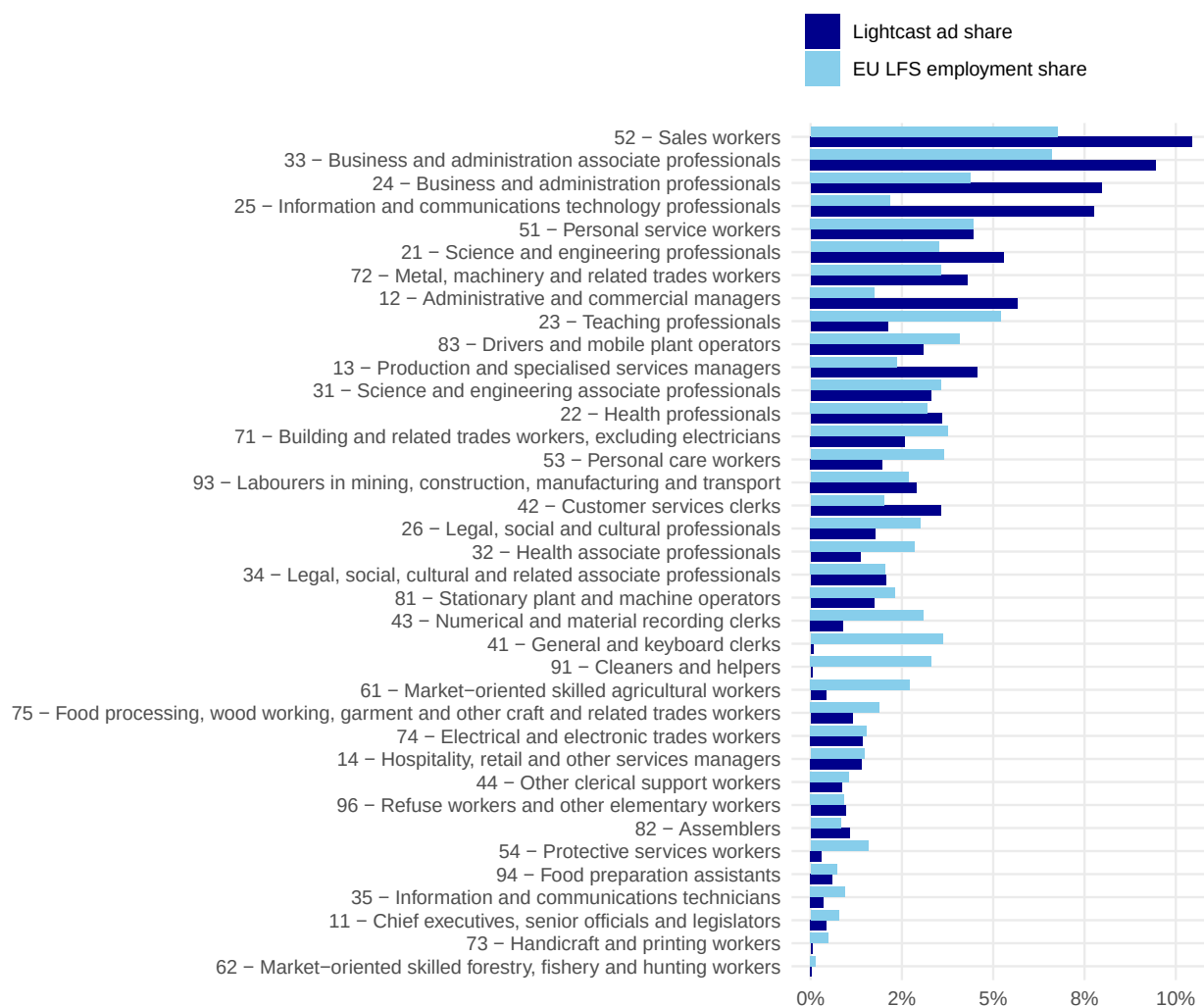
Notes: This table shows the number of job ads for each country (2018-2023) in levels and as a share of total ads across all 12 countries that enter the estimating sample. The fourth column shows each country's share of total employment across all 12 countries (avg. 2018-2023) as given by Labour Force Surveys.

Table A.4: 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.

Table A.5: 2-digit ISCO occupation shares and ad counts: Lightcast vs. Labour Force Surveys.
Wage sample

2-digit ISCO Occupation	Ad count	Unweighted ad share	LFS share
11 – Chief executives, senior officials and legislators	90,530	0.4%	0.9%
12 – Administrative and commercial managers	769,728	3.7%	1.5%
13 – Production and specialised services managers	642,422	3.1%	2%
14 – Hospitality, retail and other services managers	223,949	1.1%	1.4%
21 – Science and engineering professionals	816,422	3.9%	3.7%
22 – Health professionals	737,136	3.5%	3.2%
23 – Teaching professionals	564,626	2.7%	5.9%
24 – Business and administration professionals	1,221,995	5.9%	4.5%
25 – Information and communications technology professionals	798,533	3.8%	2.2%
26 – Legal, social and cultural professionals	255,915	1.2%	3.3%
31 – Science and engineering associate professionals	687,834	3.3%	4.5%
32 – Health associate professionals	222,589	1.1%	3.6%
33 – Business and administration associate professionals	1,674,603	8.1%	7.9%
34 – Legal, social, cultural and related associate professionals	413,346	2%	2.3%
35 – Information and communications technicians	70,744	0.3%	1.1%
41 – General and keyboard clerks	15,914	0.1%	0.2%
42 – Customer services clerks	773,299	3.7%	2.3%
43 – Numerical and material recording clerks	176,179	0.8%	3.8%
44 – Other clerical support workers	238,585	1.1%	1%
51 – Personal service workers	1,310,345	6.3%	5.2%
52 – Sales workers	2,642,024	12.7%	7.4%
53 – Personal care workers	607,454	2.9%	3.5%
54 – Protective services workers	74,870	0.4%	1.7%
61 – Market-oriented skilled agricultural workers	102,469	0.5%	2.3%
62 – Market-oriented skilled forestry, fishery and hunting workers	5,332	0%	0.1%
71 – Building and related trades workers, excluding electricians	706,597	3.4%	4.3%
72 – Metal, machinery and related trades workers	993,610	4.8%	4.2%
73 – Handicraft and printing workers	8,807	0%	0.5%
74 – Electrical and electronic trades workers	363,823	1.8%	1.8%
75 – Food processing, wood working, garment and other craft and related trades workers	243,184	1.2%	2%
81 – Stationary plant and machine operators	538,832	2.6%	1.6%
82 – Assemblers	396,814	1.9%	0.9%
83 – Drivers and mobile plant operators	984,785	4.7%	4.4%
91 – Cleaners and helpers	10,924	0.1%	0.1%
93 – Labourers in mining, construction, manufacturing and transport	996,732	4.8%	3%
94 – Food preparation assistants	153,362	0.7%	0.8%
96 – Refuse workers and other elementary workers	233,255	1.1%	0.9%

Notes: This table depicts job ads (total number and share of all ads) for each 2-digit ISCO occupation across the 12 countries that enter the estimating sample. For comparison, the LFS share column shows each occupation's share of total employment across these countries according to Labour Force Surveys.

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.	<i>Climate or Green; Not Climate, Not Green.</i>	Items labeled <i>Climate or Green</i> .
2	Title plus description.	<i>Decarbonization-energy; Decarbonization-transport; Decarbonization-buildings; Decarbonization-industry; Climate-CCS; Climate-adaptation; Climate-general; Waste-management; Forestry-ecosystem-management; Not-climate-nor-green-related.</i>	Items assigned one of the nine green types.
3	Title plus description.	<i>Too broad or too vague; Specific climate or green.</i>	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: de-carbonisation 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 be 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}.

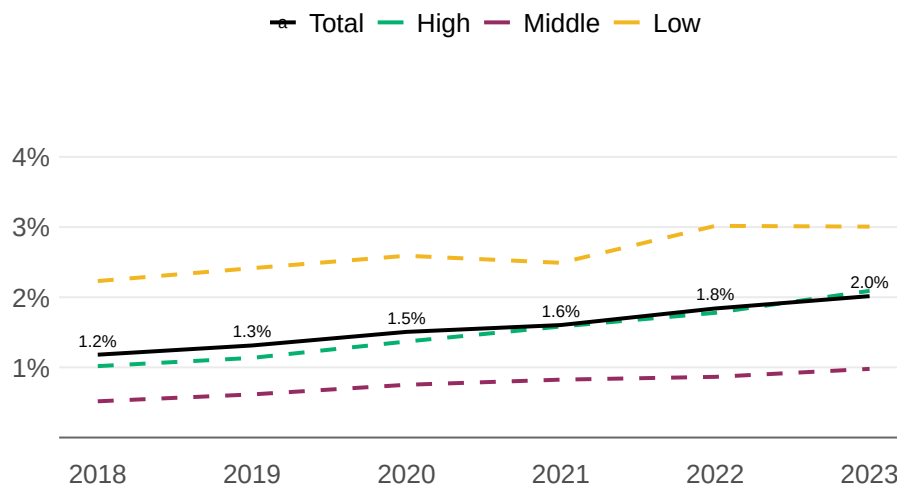
Is this occupation title broad, beyond the specific pursuit of climate or green objectives (e.g. sewage systems, generic agricultural science, generic energy-related technologies, etc.), or too vague to be characteristic? If that is the case, you should label the occupation title as “Too broad or too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

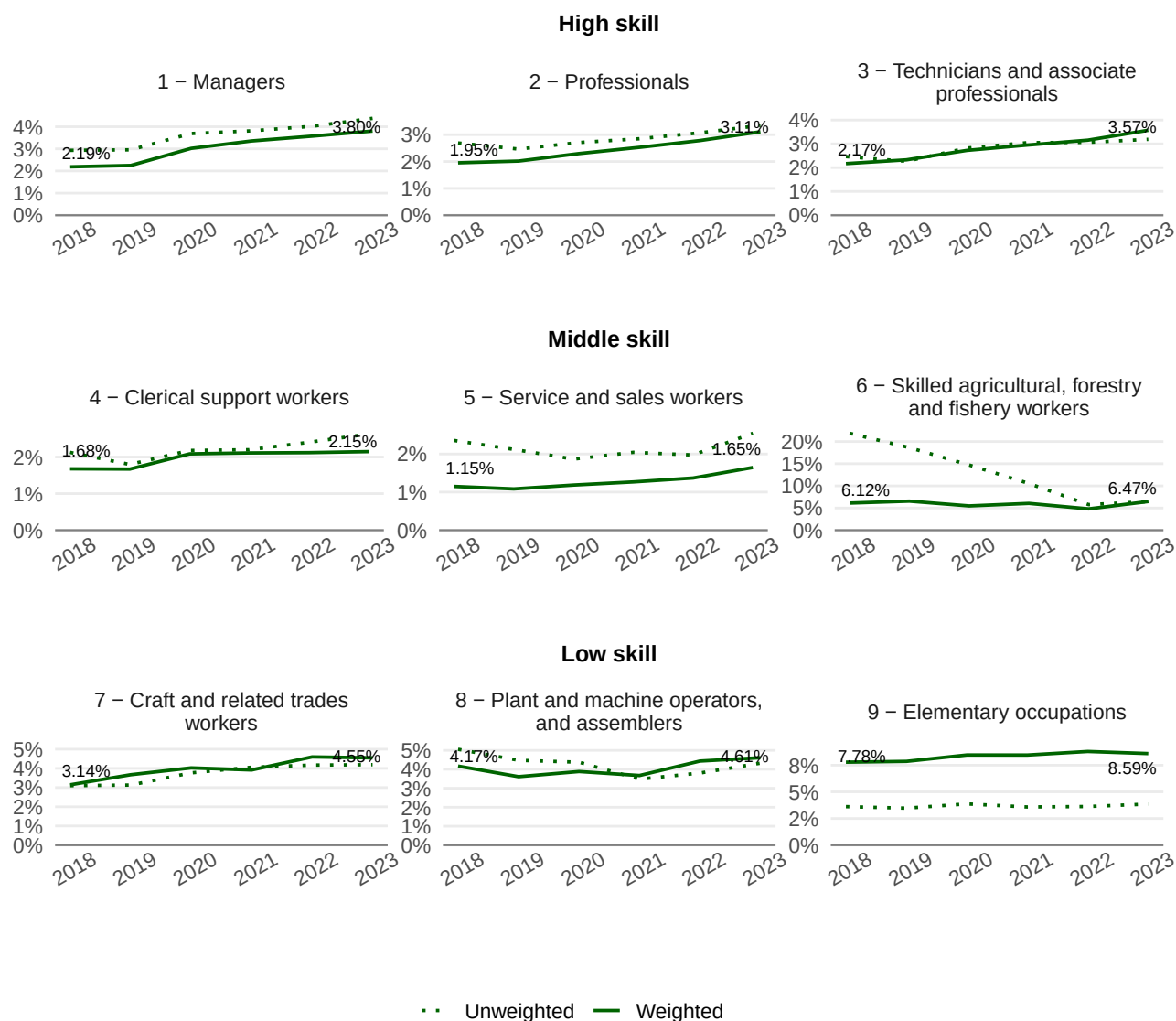
C.1 Occupational distribution

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

1-digit ISCO Occupation	Total ads	Green job share	
		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.

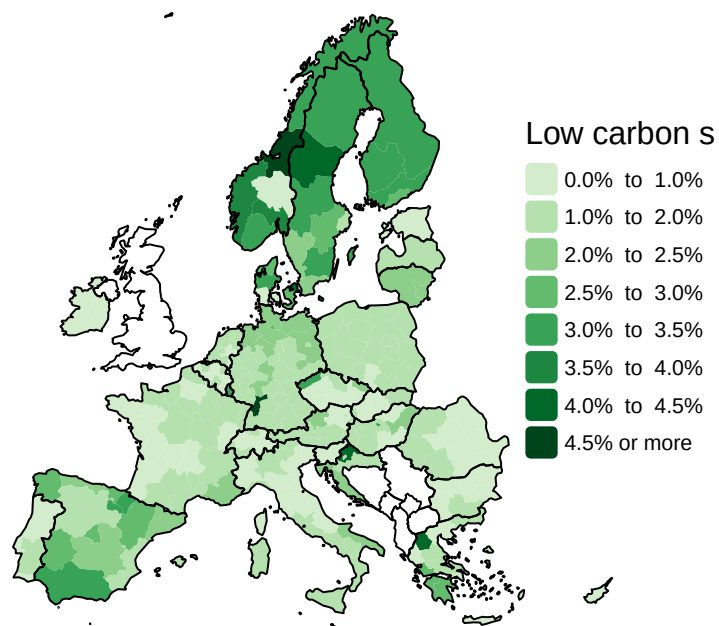
C.3 Country and regional variation

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 Descriptive statistics for the wage sample

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.³³

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.³⁴

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

³³Lightcast 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 total to 1,198. Table D.4 compares green job shares using only the first crosswalk versus both.

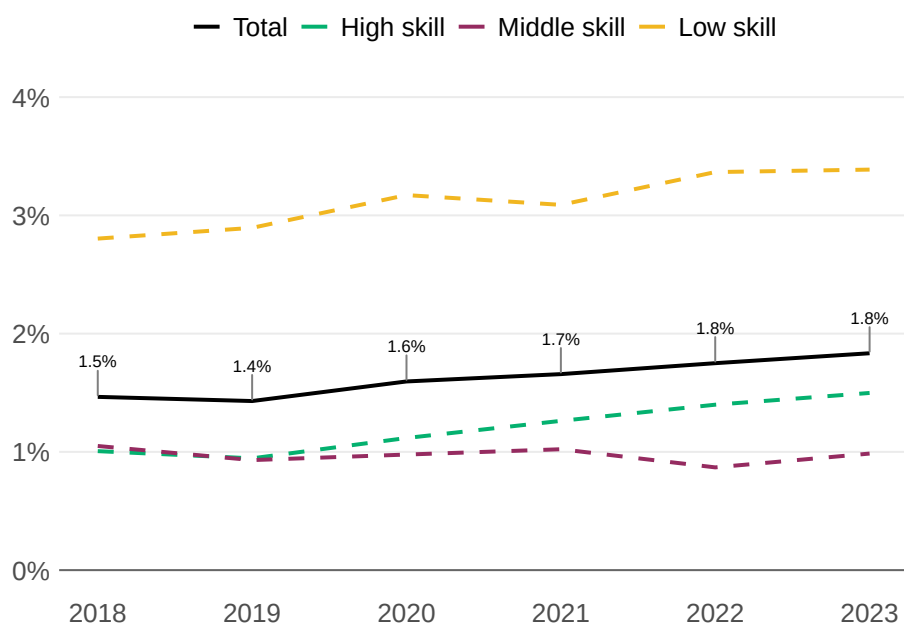
³⁴The Lightcast skill “Enthusiasm” maps to the ESCO green skills “inspire enthusiasm for nature” and “exude enthusiasm during the action sessions”, highlighting the inherent difficulty of mapping Lightcast skills to ESCO skills, which are often very task-specific

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).

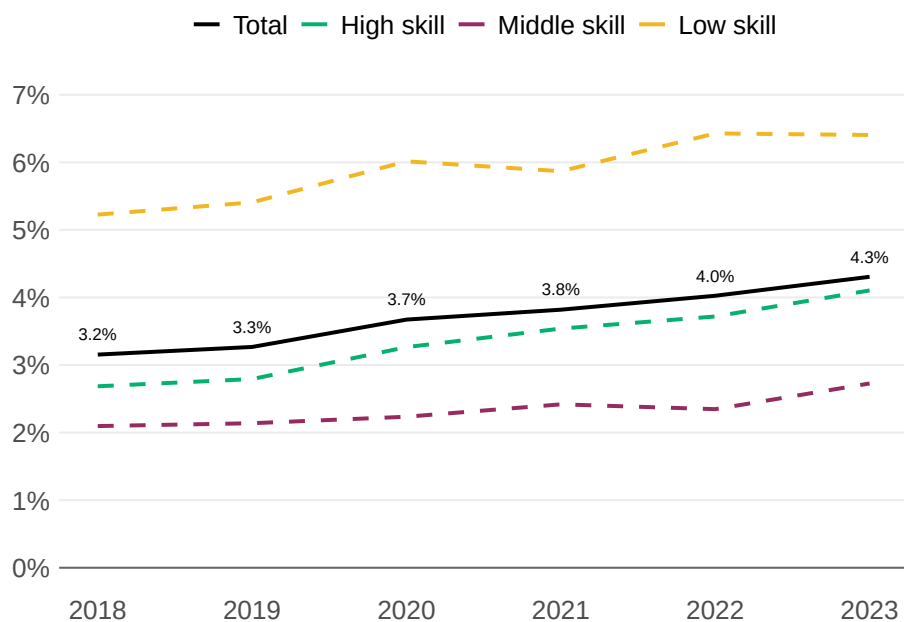
Evolution over time: Figure D.5 shows the evolution of green job shares from 2018 to 2023 under our classification and the ESCO definition. Both display a gradual upward trend: our weighted green share rises from 2.6% to 3.6%, while ESCO’s rises from 11.7% to 13.2%. Figure D.6 shows a similar comparison 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	<i>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</i>
Environmental Protection	 321,397	<i>Protection from natural elements, Implement environmental protection measures</i>
Pollution Prevention	 299,617	<i>Adopt ways to reduce pollution, Advise on pollution prevention, Pollution prevention, Prevent marine pollution</i>
Renewable Energy	 269,485	<i>Offshore renewable energy technologies, Renewable energy technologies</i>
Ecosystem Science	 194,600	<i>Ecosystems</i>
Only ESCO green classification		
Packaging And Labeling	 2,559,735	<i>Pack leather, Check bottles for packaging, Ensure correct goods labelling</i>
Tourism	 2,188,624	<i>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</i>
Enthusiasm	 2,136,740	<i>Inspire enthusiasm for nature, Exude enthusiasm during the action sessions</i>
Biology	 1,039,715	<i>Teach biology, Biology</i>
Lean Manufacturing	 927,738	<i>Lean manufacturing</i>
Only this paper's green classification		
Commuter Rail	 284,400	<i>Rail infrastructure</i>
Silviculture	 262,546	<i>Floriculture</i>
Public Transport	 257,451	<i>Promote public transport</i>
Rail Transport	 216,866	<i>Freight transport methods</i>
Electric Vehicles	 129,400	<i>Electric drives</i>

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%

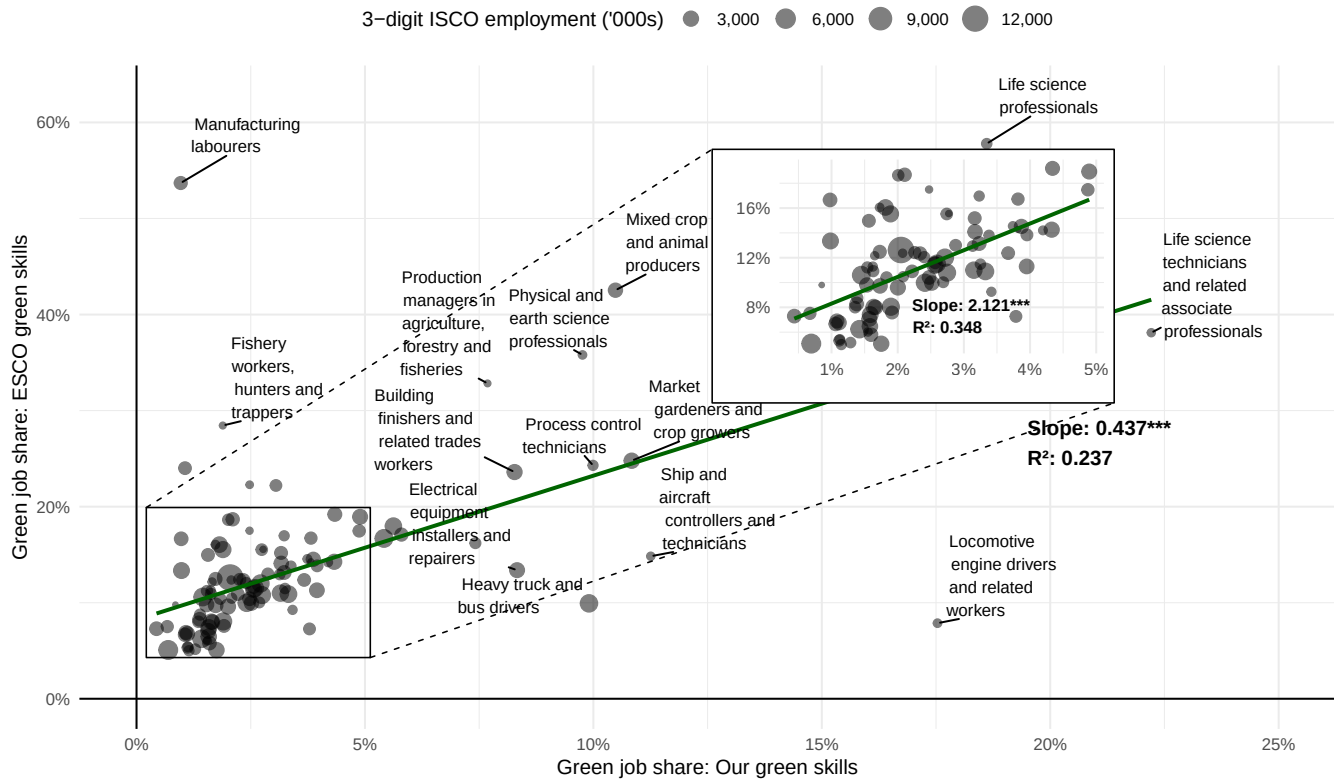
Notes: Jobs are classified as green if they have at least one skill from Lightcast's own list (or our list) of green skills. Weighted green job shares use country-specific 3-digit ISCO employment as weights.

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%

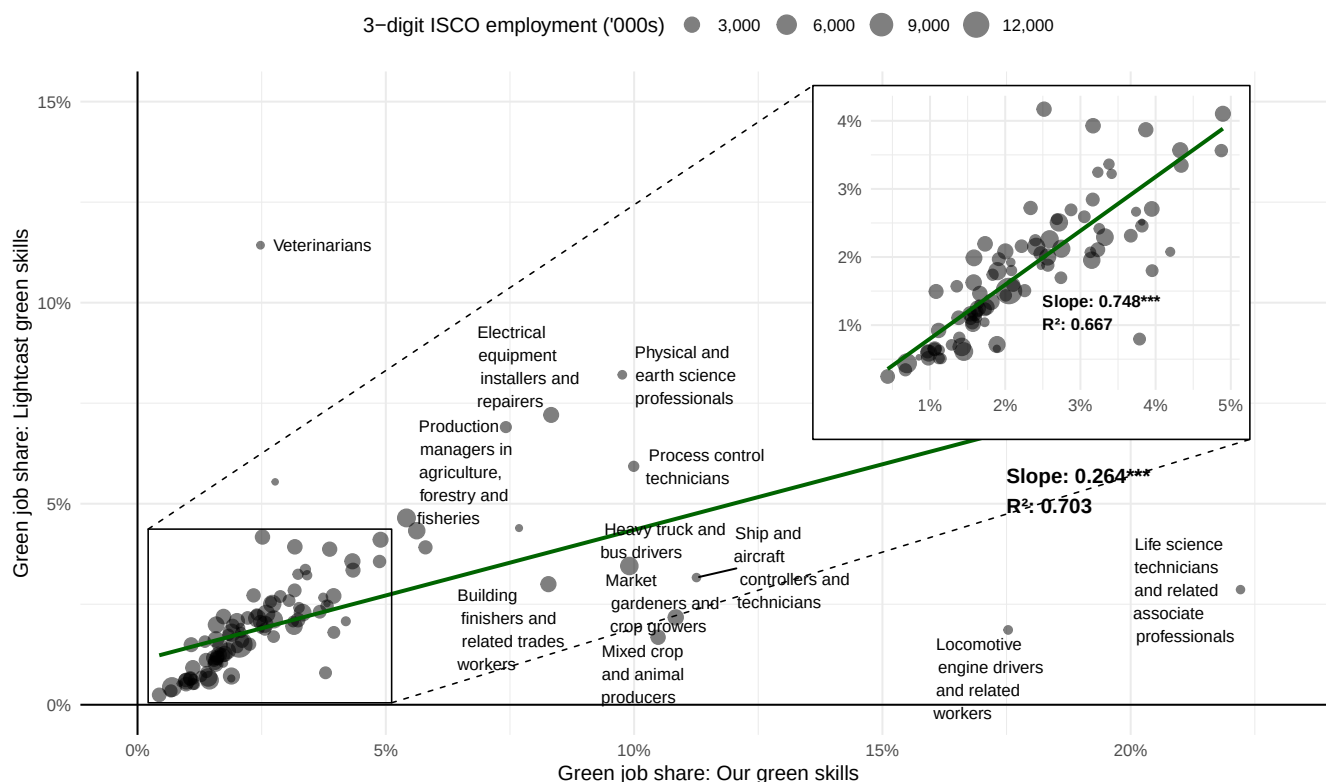
Notes: Jobs are classified as green if they have at least one ESCO green skill (ESCO version 1.1.1). “ESCO2LOT” columns use the ESCO to Lightcast skills crosswalk supplied by Lightcast; “Both crosswalks” use this crosswalk as well as the Lightcast to ESCO crosswalk, which increases the number of ESCO-classified 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



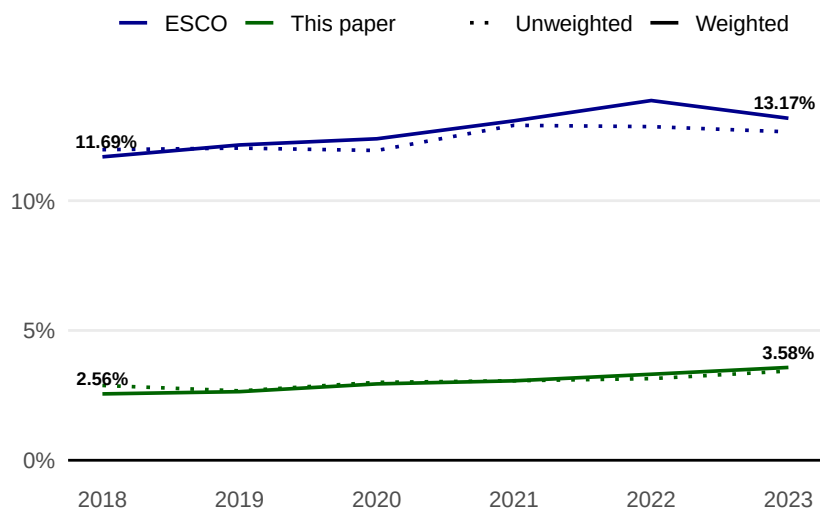
Notes: Jobs are classified as green if they have at least one skill from ESCO's green skills collection (version 1.1.1) or from this paper's own green skills classification. Bubble size reflects total 3-digit ISCO employment across all countries (EU 27 plus Norway and Switzerland) averaged over 2018-2023. 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



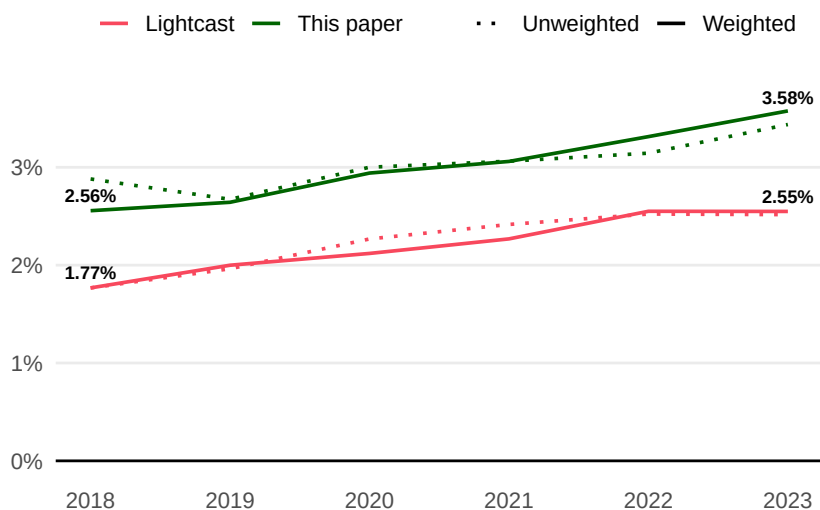
Notes: Jobs are classified as green if they have at least one skill from Lightcast's own list (or our list) of green skills. Bubble size reflects total 3-digit ISCO employment across all countries (EU 27 plus Norway and Switzerland) averaged over 2018-2023. The line of best fit is estimated using OLS 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 (SMI-CoP)	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

Continued on next page

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 (SE-BAL)	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

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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*** (0.006)	0.091*** (0.006)	0.067*** (0.004)
Country $\times$ 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 $\times$ 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*** (0.004)	0.045*** (0.004)	0.040*** (0.002)
Country $\times$ 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

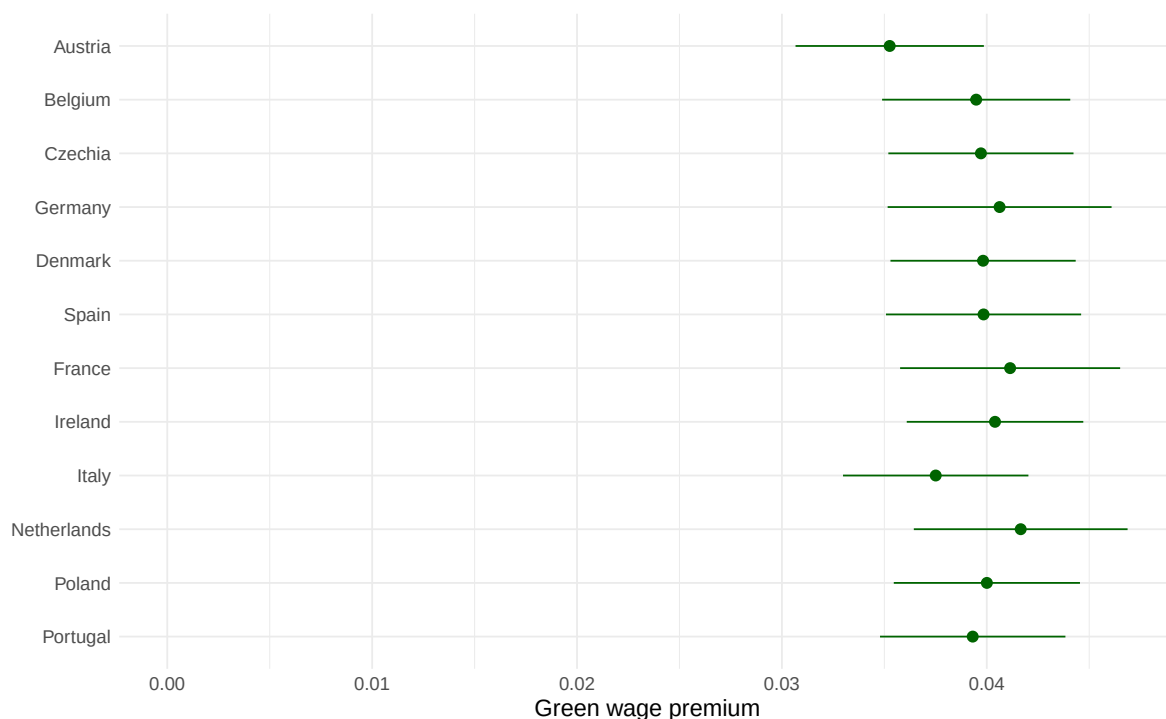
Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The dependent variable is the logarithm of the posted annual salary. Green job is a dummy equal to one if the job posting is classified as green. Column (1) includes country $\times$ 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*** (0.005)	0.077*** (0.005)	0.055*** (0.004)
Country $\times$ 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 $\times$ 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 $\times$ 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*** (0.022)	0.077*** (0.022)	0.055*** (0.016)
Country $\times$ 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 $\times$ 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*** (0.005)	0.077*** (0.005)	0.055*** (0.004)	0.056*** (0.004)
Country $\times$ 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) $\times$ 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 $\times$ 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 $\times$ 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*** (0.007)	0.097*** (0.007)	0.079*** (0.006)
Country $\times$ 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 $\times$ 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*** (0.009)	0.054*** (0.009)	0.067*** (0.008)
Green job - 2019	0.089*** (0.010)	0.094*** (0.010)	0.098*** (0.009)
Green job - 2020	0.073*** (0.008)	0.076*** (0.008)	0.062*** (0.007)
Green job - 2021	0.046*** (0.010)	0.048*** (0.010)	0.016* (0.008)
Green job - 2022	0.097*** (0.006)	0.098*** (0.006)	0.059*** (0.005)
Green job - 2023	0.075*** (0.007)	0.076*** (0.006)	0.054*** (0.005)
Country $\times$ 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 $\times$ 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*** (0.032)	0.289*** (0.042)	0.115*** (0.026)
Green job - Services	0.087*** (0.008)	0.091*** (0.008)	0.085*** (0.007)
Green job - Primary	-0.093** (0.036)	-0.069** (0.031)	-0.027 (0.032)
Green job - Manufacturing	0.069*** (0.012)	0.066*** (0.012)	0.038*** (0.011)
Green job - Construction	0.051*** (0.014)	0.050*** (0.014)	0.046*** (0.010)
Country $\times$ 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 $\times$ 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*** (0.006)	0.045*** (0.005)	0.029*** (0.005)
Green job - ISCO 8 - Plant and machine operators, and assemblers	0.053*** (0.008)	0.053*** (0.006)	0.030*** (0.006)
Green job - ISCO 7 - Craft and related trades workers	0.026*** (0.007)	0.026*** (0.006)	0.025*** (0.006)
Green job - ISCO 6 - Skilled agricultural, forestry and fishery workers	0.007 (0.012)	0.014 (0.012)	0.018 (0.013)
Green job - ISCO 5 - Service and sales workers	0.105*** (0.010)	0.111*** (0.009)	0.106*** (0.009)
Green job - ISCO 4 - Clerical support workers	0.068*** (0.011)	0.069*** (0.010)	0.074*** (0.009)
Green job - ISCO 3 - Technicians and associate professionals	0.081*** (0.007)	0.083*** (0.007)	0.067*** (0.007)
Green job - ISCO 2 - Professionals	0.041*** (0.008)	0.039*** (0.008)	0.044*** (0.009)
Green job - ISCO 1 - Managers	-0.007 (0.013)	-0.004 (0.012)	-0.012 (0.012)
Country $\times$ 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 $\times$ 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*** (0.006)	0.046*** (0.005)	0.028*** (0.005)
Green job - ISCO 8 - Plant and machine operators, and assemblers	0.050*** (0.008)	0.051*** (0.006)	0.026*** (0.006)
Green job - ISCO 7 - Craft and related trades workers	0.027*** (0.006)	0.027*** (0.006)	0.025*** (0.006)
Green job - ISCO 6 - Skilled agricultural, forestry and fishery workers	0.001 (0.012)	0.010 (0.012)	0.011 (0.013)
Green job - ISCO 5 - Service and sales workers	0.053*** (0.011)	0.061*** (0.013)	0.064*** (0.009)
Green job - ISCO 4 - Clerical support workers	0.068*** (0.011)	0.069*** (0.010)	0.073*** (0.009)
Green job - ISCO 3 - Technicians and associate professionals	0.082*** (0.007)	0.083*** (0.007)	0.068*** (0.007)
Green job - ISCO 2 - Professionals	0.041*** (0.008)	0.039*** (0.008)	0.044*** (0.009)
Green job - ISCO 1 - Managers	-0.007 (0.013)	-0.004 (0.012)	-0.012 (0.012)
Country $\times$ 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 $\times$ 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, excluding the top 10 advertising firms in each country

	(1)	(2)	(3)
Green job	0.037*** (0.006)	0.037*** (0.006)	0.029*** (0.005)
Country $\times$ 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 $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 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 $\times$ 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 $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01.

Table E.12: Low-carbon wage premium estimates, non-monetary job ad attributes and firm fixed effects

	(1)	(2)	(3)	(4)
Low-carbon job	0.074*** (0.005)	0.071*** (0.005)	0.037*** (0.009)	0.036*** (0.009)
Country $\times$ 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	15,742,224	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 $\times$ 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 firm level. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.13: 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*** (0.006)	0.078*** (0.006)	0.035*** (0.004)	0.034*** (0.004)
Country $\times$ 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 $\times$ 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.14: 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*** (0.004)	0.065*** (0.004)	0.035*** (0.002)	0.035*** (0.002)
Country $\times$ 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 $\times$ 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: Fast-growing green skills (identified on the US dataset, with firm FEs)

	(1)	(2)	(3)	(4)
Green job	0.050*** (0.004)	0.047*** (0.004)	0.028*** (0.007)	0.028*** (0.007)
Green job (emerging)	0.082*** (0.007)	0.080*** (0.007)	0.016 (0.010)	0.015 (0.010)
Country $\times$ 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	15,742,224	15,742,224	15,742,224	15,742,224
R^2	0.28	0.28	0.56	0.56

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: The table reports OLS estimates of the association between green job postings and log advertised salaries at the job-ad level. The 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. Green job (fast-growing) is a dummy equal to one if the posting contains at least one green task identified as fast-growing. All specifications include country $\times$ year, NUTS-2 region, 3-digit ISCO occupation, and part-time fixed effects. Column (2) adds non-monetary job attribute fixed effects. 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. Fast-growing green tasks are identified using US OJV data over 2010–2019 (see footnote 23 for details). 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.16: 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*** (0.013)	-0.039*** (0.005)	0.081*** (0.030)	-0.035 (0.028)
Cooperation	0.045*** (0.013)	0.045*** (0.005)	0.030 (0.019)	0.010 (0.007)
Purpose	0.012 (0.030)	-0.059*** (0.014)	0.024 (0.025)	-0.035* (0.019)
Independence	0.018 (0.018)	0.078*** (0.004)	-0.006 (0.020)	0.053*** (0.005)
Creativity	0.080*** (0.016)	0.063*** (0.004)	0.048** (0.019)	0.032*** (0.005)
Cognitive	0.027** (0.011)	0.074*** (0.004)	0.031 (0.021)	0.049*** (0.004)
IT	0.056*** (0.009)	0.057*** (0.003)	0.022* (0.012)	0.033*** (0.007)
Management	0.046*** (0.010)	0.078*** (0.003)	0.024* (0.013)	0.059*** (0.009)
Social	0.108*** (0.010)	0.025*** (0.003)	0.049** (0.022)	0.017 (0.017)
Technical	0.050*** (0.009)	0.082*** (0.003)	0.029** (0.013)	0.048*** (0.005)
Country $\times$ 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 $\times$ 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 in the specification without firm fixed effects, and at the firm level in the specification with firm fixed effects. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.4 Oaxaca-Blinder decomposition

Table E.17: 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)
<i>Endowments</i>				
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)
<i>Coefficients</i>				
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)
<i>Interaction</i>				
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 $\times$ 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 $\times$ 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) $\times$ 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	<i>Teamwork, Coaching, Cooperation, Team Oriented, Humility, Politeness, Sincerity, Social Intelligence, Community Leadership</i>
Creativity	<i>Innovation, Creativity, Imagination, Intellectual Curiosity, Creative Thinking, Visionary, Creative Strategies, Creative Entrepreneurship</i>
Managerial	<i>Planning, Leadership, Organizational Skills, Influencing Skills, Decision Making, Entrepreneurship, Strategic Planning, Supervision, Positive Management Leadership</i>
Purpose-oriented	<i>Strong Work Ethic, Honesty, Stewardship, Intercultural Competence, Personal Integrity, Cultural Responsiveness</i>
Soft skills	<i>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</i>
Work independently	<i>Self-Motivation, Time Management, Proactivity, Ability To Meet Deadlines, Results Focused, Entrepreneurship, Goal-Oriented, Self-Discipline, Self-Confidence, Independent Thinking, Smart Work</i>

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	<i>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</i>
IT	5008	<i>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)</i>
Management	848	<i>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</i>
Social	178	<i>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</i>
Technical	236	<i>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</i>

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 Returns to skills

Table F.4: Low-carbon wage premium estimates, controlling for skill types in job ad

	(1)	(2)	(3)	(4)	(5)	(6)
Low-carbon job	0.074*** (0.005)	0.071*** (0.005)	0.057*** (0.005)	0.037*** (0.009)	0.036*** (0.009)	0.029*** (0.010)
Country $\times$ 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	15,742,224	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 $\times$ 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 in columns (1), (2) and (3), and at the firm level in columns (4), (5), (6). Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.5: 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*** (0.006)	0.078*** (0.006)	0.064*** (0.006)	0.035*** (0.004)	0.034*** (0.004)	0.027*** (0.004)
Country $\times$ 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 $\times$ 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 F.6: 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*** (0.004)	0.065*** (0.004)	0.051*** (0.003)	0.035*** (0.002)	0.035*** (0.002)	0.028*** (0.002)
Country $\times$ 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 $\times$ 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 F.7: 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*** (0.011)	-0.040*** (0.005)	0.079*** (0.026)	-0.036 (0.028)
Cooperation	0.008 (0.010)	0.045*** (0.005)	0.004 (0.015)	0.011 (0.007)
Purpose	0.005 (0.021)	-0.059*** (0.014)	0.037** (0.018)	-0.036* (0.019)
Independence	0.019 (0.016)	0.078*** (0.004)	-0.006 (0.015)	0.053*** (0.005)
Creativity	0.050*** (0.012)	0.062*** (0.004)	0.029* (0.015)	0.032*** (0.005)
Cognitive	0.043*** (0.015)	0.073*** (0.004)	0.019 (0.014)	0.050*** (0.004)
IT	0.019*** (0.007)	0.057*** (0.003)	0.012 (0.009)	0.033*** (0.007)
Management	0.039*** (0.006)	0.077*** (0.003)	0.018 (0.013)	0.059*** (0.009)
Social	0.090*** (0.009)	0.024*** (0.003)	0.053*** (0.018)	0.016 (0.017)
Technical	0.033*** (0.007)	0.082*** (0.003)	0.015 (0.010)	0.048*** (0.005)
Country $\times$ 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 $\times$ 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 in the specification without firm fixed effects, while at the firm level in the specification with firm fixed effects. Number of unique firms: 221942. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.3 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 $f_{sk}^i = \frac{n_{sk}^i}{n_k^i}$, we define the green skill gap for skill group s as:

$$f_s^g - f_s^{ng} = \sum_k \omega_k^g \omega_k \times (f_{sk}^g - f_{sk}^{ng}), \quad (6)$$

where f_s^{ng} is the simple average share of job ads mentioning skill s across all occupations, ω_k^g 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.³⁵

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

$$f_s^g - f_s^{ng} = \sum_k \omega_k^g \omega_k \times [(f_{sk}^g - f_{sk}^{ng}) + (f_{sk}^{ng} - f_s^{ng})]. \quad (7)$$

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_k^g) 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.

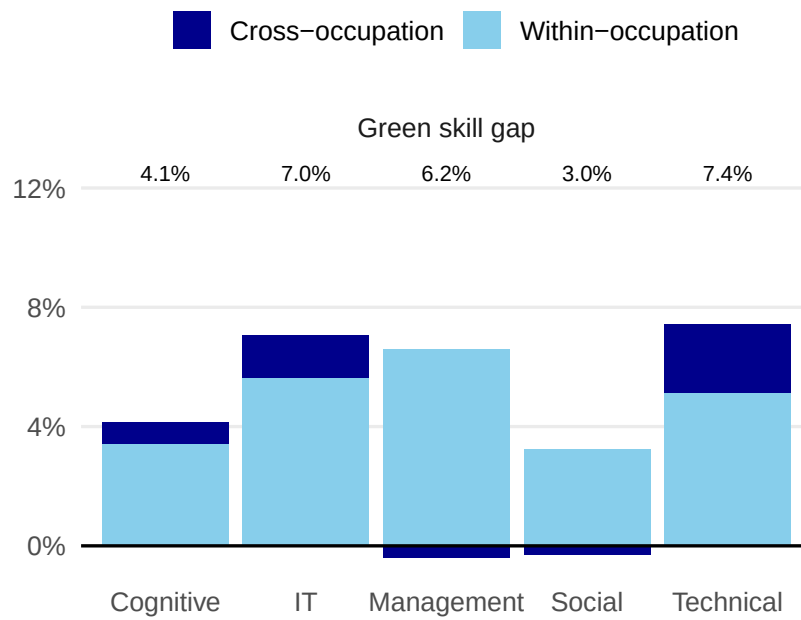
³⁵For comparability, both measures are renormalized such that $\sum_k \omega_k^g \times \omega_k = 1$. This ensures that $f_s^g - f_s^{ng}$ can be interpreted as the average skill gaps across occupations at 3-digits.

Table F.8: Within- vs cross- occupation green skill gap

Green share $\times$ 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.4 Skill gap regressions robustness

Table F.9: Extensive margin green skill gap between green and non-green jobs, unweighted

	(1)	(2)	(3)
Panel A: Broad skills			
Green job - Cognitive	0.030*** (0.002)	0.027*** (0.002)	0.016*** (0.001)
Green job - IT	0.071*** (0.004)	0.055*** (0.003)	0.033*** (0.002)
Green job - Management	0.063*** (0.004)	0.071*** (0.003)	0.046*** (0.002)
Green job - Social	0.029*** (0.003)	0.034*** (0.002)	0.017*** (0.002)
Green job - Technical	0.062*** (0.003)	0.042*** (0.003)	0.030*** (0.003)
Panel B: Non-monetary job attributes			
Green job - Cooperation	0.004*** (0.001)	0.006*** (0.001)	0.004*** (0.001)
Green job - Creativity	0.029*** (0.002)	0.031*** (0.002)	0.018*** (0.001)
Green job - Independence	0.007*** (0.002)	0.008*** (0.002)	0.003*** (0.002)
Green job - Purpose	-0.001** (0.000)	-0.000 (0.000)	-0.001 (0.000)
Green job - Soft skills	-0.000 (0.002)	0.009*** (0.002)	0.007*** (0.002)
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	0.05	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.10: 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*** (0.002)	0.023*** (0.002)	0.018*** (0.002)
Low-carbon job - IT	0.080*** (0.006)	0.057*** (0.005)	0.035*** (0.004)
Low-carbon job - Management	0.044*** (0.006)	0.057*** (0.005)	0.052*** (0.005)
Low-carbon job - Social	0.028*** (0.004)	0.032*** (0.004)	0.026*** (0.002)
Low-carbon job - Technical	0.075*** (0.004)	0.057*** (0.003)	0.043*** (0.003)
Panel B: Non-monetary job attributes			
Low-carbon job - Cooperation	0.002 (0.001)	0.003** (0.001)	0.003*** (0.001)
Low-carbon job - Creativity	0.025*** (0.003)	0.025*** (0.002)	0.017*** (0.002)
Low-carbon job - Independence	0.003*** (0.001)	0.003*** (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*** (0.002)	0.000 (0.002)	0.006*** (0.002)
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 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.

The Local Job Multipliers of Green Industrialisation.*

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Abstract

What are the job multipliers of the green industrialisation? We tackle this question within EU regions over the period 2003-2017, building a novel measure of green manufacturing penetration that combines green production and regional employment data. We estimate local job multipliers of green manufacturing penetration in a long-difference model, using a shift-share instrument that exploits plausibly exogenous changes in non-EU green innovation. We find that a three-year change in green manufacturing penetration per worker increases the employment-to-active population ratio by 0.11 percentage points. The effect is: persistent both in manufacturing and outside manufacturing; halved by agglomeration effects that increase the labour market tightness; stronger for workers with high and low education; and present also in regions specialized in polluting industries. When focusing on large shocks in a staggered difference-in-differences design, we find ten-times larger effects, particularly in earlier periods.

Keywords: Green industrialisation, Local job multipliers, Employment effects, Green transition, Shift-share IV, Difference-in-differences.

JEL: J21, O14, R11.

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1 Introduction

Green deal plans are popular around the world and aim to reconcile employment growth and the transition to carbon neutrality, through coordinated investments in infrastructure, skills, and specific industries (Rodrik, 2014; Tagliapietra and Veugelers, 2020). A key element of this new strategy is to foster green industrial production, e.g., electric vehicles, batteries and PV panels, and promote re-shoring of associated value chains through local content requirements. Although the logic of green deal plans is clear and resonates with that of a so-called “Big Push” (Rosenstein-Rodan, 1943; Murphy et al., 1989), there is not much evidence in support of the claim that green industrialisation creates a large number of well-paid jobs.

This paper contributes to this debate by providing novel evidence on the effect of green industrialisation on employment growth for EU (NUTS2) regions over the period 2003-2017. EU countries are an interesting case to study the effect of green industrialisation on local labour markets. On the one hand, European countries gradually lost their comparative advantage in specific green productions in favour of China. On the other hand, EU governments are planning to implement a combination of trade tariffs, local content requirements, and industrial subsidies to re-shore green production, for example through the Net Zero Industry Act (NZIA). Given the wide local effects of manufacturing activities, we estimate both direct effects on manufacturing and indirect local-multiplier effects (Moretti, 2010). We build a novel measure of Green Regional Penetration (henceforth GRP) that combines granular country-product data on green industrial production (Bontadini and Vona, 2023; Frattini et al., 2024) with regional employment shares disaggregated across 2-digit manufacturing industries. Specifically, we allocate green production changes to regions using their lagged industrial structure (Autor et al., 2013). In essence, GRP proxies for regional exposure to changes in green industrial production.

To address endogeneity concerns in GRP, we use a shift-share instrumental variable (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), which leverages technology improvements in non-EU countries combined with regions’ initial green capabilities to identify plausibly exogenous variation in the production of green goods locally. The intuition is that regions with stronger initial green capabilities can better exploit global improvements in green technologies to activate or expand green production.¹ This supply-side approach, common in studies of renewable energy generation (Fabra et al., 2024; Scheifele and Popp, 2025), isolates technology-driven variation rather than policy shocks.

In a first-difference model, our favourite shift-share specification reveals that GRP shocks positively

¹This strategy is conceptually aligned with shift-share instrumental variables that leverage exposure to technological shocks to study long-term employment dynamics in local labour markets (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020; Acemoglu et al., 2022).

affect total regional employment-to-(economically) active population ratio. Interpreting our effects as Local Average Treatment Effect (LATE), we quantify their economic relevance using the variation in green production explained by the shift-share instrument. GRP raises employment-to-active population by approximately one-tenth of a percentage point (0.11 p.p.) after three years. The modest size of the effect is in line with the fact that green manufacturing production is modest itself (around 3%). Decomposing the effect by sectors shows that new jobs are created both in manufacturing (the “treated” sector) and in non-manufacturing activities (the pure multiplier effects). However, while the former effect is persistent, the latter fades away in the long-run, i.e., after five years. Within non-manufacturing sectors, we find substantial heterogeneity, with positive impacts for construction and utilities and null ones on the service sector.

Inspecting a longer time profile of the multiplier effect, we examine employment (numerator) and active-population (denominator) separately. A positive effect of GRP on active population, i.e., an agglomeration effect that increases the tightness of local labour markets, counteracts the long-term effect of GRP on employment. When netting out this agglomeration effect, estimates reveal that GRP shocks affects also non-manufacturing employment in the long-term. Moreover, in line with previous research (Vona et al., 2018; Popp et al., 2021), our estimates reveal that the greening of labour markets exacerbates job polarization, as the positive effect of GRP shocks is concentrated on workers with tertiary education, especially those employed in STEM—Science, Technology, Engineering and Mathematics— jobs, and basic education (lower-secondary or less), particularly in the construction sector.

A possible threat to the plausibility of our identification strategy is the violation of the parallel trend assumption. In a shift-share instrumental variable design such a violation is difficult to detect, given that the instrument is a linear combination of multiple instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).² Following Goldsmith-Pinkham et al. (2020), we apply the most recent diagnostic tests for shift-share instrumental variable designs to detect the potential presence of pre-trends for the whole instrument and its components, i.e., the baseline employment shares of the 2-digit NACE (Rev. 2) sectors that receive the highest Rotemberg weights in the instrument. Overall, these diagnostic tests indicate that severe pre-trends do not undermine the credibility of our favourite specifications. We lend further credibility to our research design by providing formal tests of the relevance of the instrumental variable (Lee et al., 2022) and the validity of the monotonicity assumption.³ Then, we address the concern that GRP shocks may partly reflect variation in regional

²Violations of the parallel trend assumptions are a key issue in the related paper of Popp et al. (2021), where regions receiving more green subsidies under the American Recovery and Reinvestment Act were also growing faster before the policy.

³Lending support to the monotonicity assumption is necessary in our setting because green innovation shocks in other

employment structure rather than true differences in green production intensity, and we replicate the analysis at the country-level. Estimates remain in line with the regional ones, and about double in magnitude (one fourth of a percentage point, 0.25 p.p.). This is in line with Chodorow-Reich (2020), who shows that regional regressions typically identify partial-equilibrium local effects, while the aggregate employment effect can be larger due to positive general-equilibrium spillovers, especially when the monetary policy does not react. Finally, we conduct a series of additional robustness checks, such as checking the sensitivity of our results to the inclusion of different sets of controls, including automation exposure, population density and demographic characteristics, to different sets of fixed effects, alternative clustering levels, and the presence of outliers. Our evidence is robust across the board.

We extend our main results in two policy-relevant directions. First, we simulate what could happen with a big green push by investigating the effect of large GRP shocks, which serve as a better proxy for a policy-driven fiscal stimulus, in a staggered difference-in-differences design (Roth et al., 2023). The effect of such a shock on total employment is approximately ten times larger than the LATE effect, which is not surprising given the larger size of the shocks and the fact that we estimate an Average Treatment Effect on the Treated (ATT) rather than a LATE. Moreover, the effects of large GRP shocks are persistent on non-manufacturing employment, even without purging from possible agglomeration effects. Importantly, these effects seem not invalidated by the presence of pre-trends. Lastly, by decomposing the ATT in cohort-specific effects (Callaway and Sant’Anna, 2021), we find that early shocks have significantly larger employment effects. This resonates with the fact that Europe has lost his comparative advantage in critical green products, making large shocks less frequent (Liu and Goldstein, 2013; Buchholz et al., 2019).

Second, we investigate the differential effect of GRP shocks for regions more vulnerable to the green transition. In fact, it is critical to consider how the green transition would affect regions that may be poorly equipped for it. We identify such “brown” regions using the regional employment share in polluting industries at baseline. We find that green multipliers are not statistically different for browner regions. Indeed, while browner regions may have less green technological capabilities, they are usually poorer (Weber, 2020) and thus characterised by higher labour-supply elasticity (Austin et al., 2018). Notably, this null effect is not due to noise. This finding lends support to green industrial policies as a place-based policy for distressed communities in the context of the green transition (Bartik et al., 2019; Iammarino et al., 2019; Vona, 2023).

countries (the shift part of the instrument) can both increase green production in EU countries with baseline better green technological capabilities (the main assumption behind our identification strategy) or decrease them due to a competition effect.

Our study on the local employment effect of green industrialisation can be framed as a test of recent theoretical models revisiting the job creation and destruction effects of new technologies (Acemoglu and Restrepo, 2019; Gregory et al., 2022; Autor et al., 2024). These models argue that new technologies are mainly labour-saving on existing tasks, where a learning process towards standardisation has been accomplished, and labour-augmenting on new tasks, that are, by definition, ill-structured and less routinised. Previous research shows that the bulk of employment in green activities requires new tasks, either within established occupations or through the emergence of new occupations (Vona et al., 2018; Vona et al., 2019; Saussay et al., 2022; Elliott et al., 2024). Thus, green industrial production can be more labour-intensive than other kinds of production within the manufacturing sector, explaining the positive effect of GRP on manufacturing employment.⁴ Relating to the multiplier effect of GRP, the economic geography literature provides additional reasons to expect positive local multipliers. First, high and medium-tech activities, such as green ones, pay higher wages that boost local employment through pecuniary externalities (Moretti, 2011). Second, new work and innovative activities, such as green ones, are more likely to attract complementary upstream and downstream activities locally (Lin, 2011; Carlino and Kerr, 2015). In the green economy, for instance, Popp et al. (2021) and Fabra et al. (2024) show that job creation effects on construction activities are particularly important as building new infrastructures is an essential element of green industrialisation.

This paper contributes to the voluminous literature that evaluates job multiplier effects of various activities, exploiting either fiscal or supply-side shocks (Moretti, 2010; Wilson, 2012; Nakamura and Steinsson, 2014; Chodorow-Reich, 2019). A nascent literature evaluates the job multiplier effects of the green transition. The seminal study of Vona et al. (2019) follows the empirical strategy of Moretti (2010), estimating the indirect job creation effects of a new green job in US metropolitan areas. The main finding is that the green job multiplier is large compared to other sectors and in line with job multipliers of high-tech activities. Popp et al. (2021) uses similar data, but concentrates on a fiscal push, i.e. the green subsidies within the American Recovery and Reinvestment Act (ARRA). Green job multipliers appear more uncertain in this case, due to the presence of pre-trends, and become large and persistent only for regions with a greater prevalence of green skills, mostly technical and engineering ones. Wald et al. (2024) find modest multiplier effects of the French Energy Efficiency Obligations scheme, a large-scale energy retrofit programme. Taken together, these findings suggest that green job multipliers are expected to be larger for regions with better pre-existing green capabilities. We build on these findings by exploiting differential exposure to green technology shocks as a function of

⁴Although not directly examining green activities, the recent paper of Autor et al. (2024) finds that several new job titles, a measure of new task, are related to the green economy. The related paper of Saussay et al. (2025) combines the rich textual description of job vacancy data and patent abstracts to show that green technologies are more labour-augmenting than other technologies.

the initial regional capabilities, and, to the best of our knowledge, be the first to estimate the local multiplier effect of green industrialisation. We also complement US-based studies considering different countries, the entire EU, and isolating the effects of large GRP shocks.

Another strand of literature focuses on the energy sector within the green transition, covering different geographies: Spanish (Fabra et al., 2024) and Brazilian (Scheifele and Popp, 2025) municipalities, NUTS3 regions in four EU countries (Cappa et al., 2024) and the US commuting zones (Chan and Zhou, 2024).⁵ Like us, these studies use a supply-side shock, such as the building of a wind farm or renewable energy penetration, to identify local labour market effects, either in an event study setup or exploiting the local suitability to wind or solar as an instrument. While the size and the persistence of effects are mixed, the two peer-reviewed papers suggest that job creation effects are probably short-lived, stronger for solar, and concentrated in the construction phase of the plant (Fabra et al., 2024; Scheifele and Popp, 2025). Our research complements this work focusing on a larger, yet overlooked, part of the energy transition: green industrialisation. Because green goods are tradable and high-tech, we expect larger and more persistent job multipliers than those related to the renewable energy generation.

Lastly, this paper contributes to the literature on the so-called just transition. Several papers focus on the decline of coal (Weber, 2020; Hanson, 2023; Haywood et al., 2024; Rud et al., 2024), highlighting its persistent negative effects on both workers and regions. Instead of studying the decline of polluting industries, we focus on the potential solutions by examining the extent to which a green industrial push can alleviate the consequences of job losses in left-behind regions hosting pollution-intensive industries. As shown by a few recent papers in political science (Bergquist et al., 2020; Bolet et al., 2024; Cavallotti et al., 2025), giving new green opportunities to left-behind brown workers and regions is essential to enhance the political acceptability of the green transition. Our results are encouraging on the feasibility of this strategy within the EU context.

The rest of the paper is organized as follows. Section 2 describes the data used and shows a few descriptive facts. Section 3 discusses the empirical framework associated with the shift-share instrumental variable. Section 4 presents the main results, the validation of the shift-share instrumental variable, and the sensitivity of the results to different specifications. Section 5 presents the results of the two extensions. Section 6 concludes.

⁵ A parallel strand of literature focuses on the local job creation effect of fossil fuel energy (Black et al., 2005; Marchand, 2012; Weber, 2012; Feyrer et al., 2017), finding modest employment effects.

2 Data and descriptives

2.1 Measuring green production

We measure (green) manufacturing production leveraging granular product-level data from the PRODCOM dataset by Eurostat. For the manufacturing sector, the PRODCOM dataset provides detailed information on the value of production for around 4,000 products annually from 1995 to 2017.⁶ Since PRODCOM does not provide an official definition of green goods, we need a list of green products to measure green penetration. Historically, various lists of green products emerged as part of international negotiations to reduce the tariffs on a set of goods that are crucial for low-carbon transitions and sustainable development in general (WTO, 2001; Shapiro, 2021). In recent work, Bontadini and Vona (2023) identify a list of green products that reduce harmful environmental impacts in their usage, e.g., wind turbines. Their list is obtained by excluding double-usage products from a list of 902 green products contained either the OECD’s Combined List of Environmental Goods (CLEG) or the German Statistical Office’s list of green goods, which follows Eurostat’s criteria for defining environmental goods (Eurostat, 2016).

For this paper, we extend and update the list of green goods in Bontadini and Vona (2023) by applying the following changes. First, we expand the list to include a set of new products whose environmental benefits are now established.⁷ Second, we include batteries, which were excluded in the original list due to their double usage, given their growing importance in the energy transition. Third, we include nuclear energy and biofuels as they are considered part of the broad portfolio of low-carbon technologies in the official EU taxonomy. Fourth, we addressed and corrected ambiguities in the previous classification.⁸ Lastly, we broadened the scope of products to include not only final green products, but also their constituent components, with particular attention to those used in energy-efficient building.⁹ This slightly revised list contains 188 green products.¹⁰ We then aggregate the green production of each product at the 2-digit NACE-by-country-level, and deflate green and non-green production using the price indexes provided by the 2019 release of EUKLEMS.¹¹

⁶For Eastern European countries PRODCOM data are only available from 2003 onward

⁷Examples of these goods are: 2720235 Lithium-ion accumulators (excl. spent); Indicator panels incorporating light emitting diodes (LED).

⁸For example excluding goods such as 33204100 - Installation of medical and surgical equipment - and 33204200 - Installation services of professional electronic equipment.

⁹For example including goods such as 23991930 - Mixtures and articles of heat/sound-insulating materials n.e.c. - and 26405190 - LED backlight modules for LCDs of headings 8525 to 8528 (excl. for computer monitors).

¹⁰The reason why the number of green goods in the current list (188) is lower than the lists of Bontadini and Vona (2023) and Frattini et al. (2024) (221) has to do with the fact that we employ new PRODCOM data which Eurostat harmonized up to 2007, directly aggregating quite a few green goods. More details on the data cleaning process as well as the full list of green products can be found in the Appendix B.

¹¹NACE codes are nested within PRODCOM codes, making the aggregation straightforward.

2.2 Green regional penetration

While data on green production are only available at the industry-by-country level, our goal is to estimate the impact of green industrialisation on local EU labour markets, both directly (on manufacturing jobs) and indirectly (on other sectors' jobs). However, detailed data on production across industries and regions is not available for European countries.¹² To overcome this empirical challenge, we allocate country-sector green production to regions using information of the regional employment structure. Specifically, we exploit the Structural Business Statistics (SBS) data of Eurostat, which provides NUTS2 manufacturing employment at 2-digit NACE sector level, and the EU Labour Force Survey (LFS) that provides NUTS2 total employment. The measure of green regional penetration reads as follows:

$$GRP_{r,t} = \sum_j \frac{L_{rj,t}}{L_{cj,t}} \cdot \frac{GP_{cj,t}}{L_{r,t}}, \quad (1)$$

where $GP_{cj,t}$ is green production in country c , industry j , at time t . $\frac{L_{rj,t}}{L_{cj,t}}$ are the employment shares of manufacturing industry j in region r and country c at time t . Note that within-country, cross-regional differences in green production for industry j (e.g., bicycles) stem uniquely from variation in these shares. We then compute green industrialization penetration relative to the size of the local economy rescaling for the regional employment ($1/L_{r,t}$) and hence obtaining a measure of green regional penetration per worker (GRP henceforth).

Our interest lies with industrialisation shocks. Accordingly, we explore the time profile of the effect of green industrialisation by taking time differences of Equation 1 at various intervals of length k : Hence,

$$\Delta GRP_{r,t_k} = \sum_j \frac{L_{rj,t-k}}{L_{cj,t-k}} \cdot \frac{\Delta GP_{cj,t_k}}{L_{r,t-k}}, \quad (2)$$

where $\Delta GP_{cj,t_k}$ refers to the change of green production in country c , industry j , between t and $t - k$. To capture initial exposure to green shocks, the employment shares, as well as the total regional employment, refer to the initial period $t - k$. In constructing the main variable of interest $\Delta GRP_{r,t_k}$, the underlying assumption is that growth of green production in an industry at the national level is more likely to occur in regions that account for the largest share of employment in that industry. While this approach is constrained by the data availability challenges we describe above, it is consistent

¹²The European Commission Joint Research Centre (JRC) produces the ARDECO database which, however, lumps mining, manufacturing and energy provision together in a single industrial sector. The structure of business survey, which we rely on in this work, does not provide information on production by region and detailed industry, but only on employment.

with that of the China shock literature (Autor et al., 2013). Further, we assess the sensitivity to this assumption in the robustness checks section.

2.3 Green patents

We seek to isolate arguably exogenous variation in green production exploiting improvements in green technology in non-EU countries. For this purpose, we build a measure of initial exposure to green innovations using patent applications in the European Patent Office (EPO).¹³ Information on patent applications are retrieved from the PATSTAT dataset, and we treat as green all patents that contain at least one green technology class, i.e., the so-called Y02 tag under the Cooperative Patent Classification (CPC). To smoothen yearly fluctuations in patent activities and obtain an accurate proxy of green technological exposure, we construct the stock of green patent applications until year t using the perpetual inventory method (Verdolini and Galeotti, 2011).¹⁴ For each patent application, PATSTAT assigns NACE codes associated with it following Van Looy et al. (2014). The concordance by Van Looy et al. (2014) builds on Schmoch et al. (2003), and assigns CPC classes to sectors according to the dominant industrial affiliation (NACE) of patent holders.

2.4 Other variables

The dependent variables are regional employment measures: total, split by different sectors and by skill categories. To construct them, we gather data from the EU Labour Force Survey (LFS). We divide employment measures by the active population to account for the effect of green industrialisation on both job creation and labour force participation. Active population is defined as the sum of employed and unemployed people. We use LFS data for our dependent variables as SBS data—which are used to map green production shocks in manufacturing to region—do not contain information on the service sector. Moreover, we collect various data on NUTS2 characteristics to control for potential confounders in the econometric analyses, e.g., population density, share of female, foreign-born and population by educational attainment. As an additional control, in an extension, we also use data on regional exposure to automation from Anelli et al. (2021).

Our final dataset is a balanced panel of 278 NUTS2 regions for 28 countries that spans from 2003 to 2017 and contains information on the variables discussed above.¹⁵ Table A1 provides basic statistics

¹³See Popp (2019) for a recent review on the use of patents to measure green innovation.

¹⁴The formula is $K_{i,t} = PAT_{i,t} + (1 - \delta)K_{i,t-1}$, where $\delta = 0.1$ is the depreciation rate, $PAT_{i,t}$ is the number of green patents in CPC class i at time t . The initial stock (1991) is calculated as $K_{i,t_0} = PAT_{i,t_0}(1 - \delta)$.

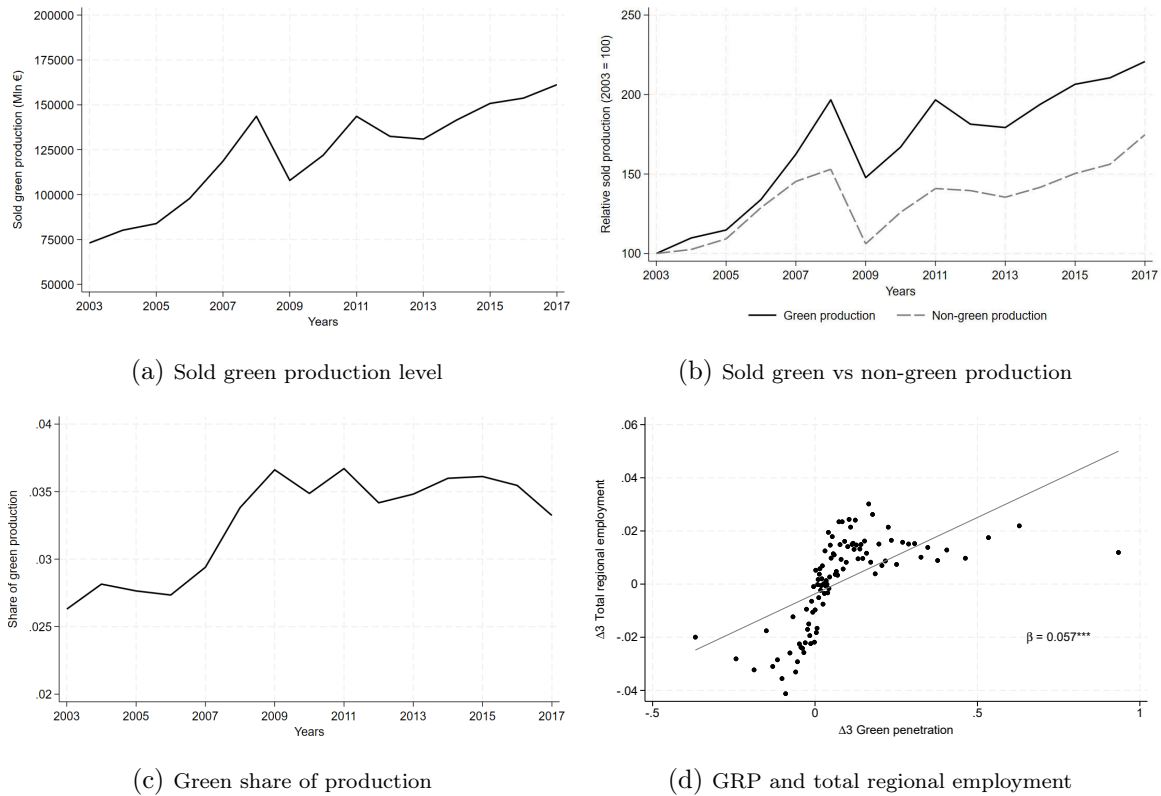
¹⁵The countries in the analysis are: AT, BE, BG, CY, CZ, DE, DK, EL, ES, FI, FR, HR, HU, IE, IS, IT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK, UK. We exclude EE and LT for data availability. Further, we exclude the following regions: FRY1 (Guadalupe); FRY2 (Martinique); FRY3 (Guayane); FRY4 (Reunion); FRY5 (Mayotte); ES70 (Canarias); PT20 (Azores); PT30 (Madeira).

related to the main data, while Appendix B provides extensive details on the construction of the final dataset.

2.5 Descriptive evidence

Our analysis spans the period 2003-2017. Figure 1 shows that EU green production exhibits an upward trend during this period (panel a). A similar upward trend is also observed for the green regional penetration (Table A1). Importantly, the long-term growth rate of green production (+120%) outperformed that of non-green production (+74%), particularly so after the 2008 financial crisis (panel b).¹⁶ Consistently with previous findings on the size of the green economy (Elliott and Lindley, 2017; Vona et al., 2019; Saussay et al., 2022), the share of green over total production remained quite small, accounting for just 3.3% in 2017 (panel c). Lastly, a three-year change in GRP positively correlates with that of regional employment (panel d). This positive unconditional correlation between green industrialisation shocks and employment growth further motivates the econometric analysis of the next section.

Figure 1: Trends in production and raw correlation of GRP and regional employment.



Notes. These plots show the evolution over time of total and green production in absolute levels in panel (a), in relative levels in panel (b), and of the share of green production in panel (c). Panel (d) shows the correlation between the three-years change in total regional employment over active population, and the three-years change in green regional penetration. We weight the two variables by the share of regional population over the EU one. Dots are binned ($n = 100$).

¹⁶ Additionally in the Appendix we show that regions attracting green productions do not do so at the detriment of non-green production (Figure A1)

Green industrial production is known to be highly concentrated in a few high-to-medium tech manufacturing sectors (Bontadini and Vona, 2023; Frattini et al., 2024, and Table A2).¹⁷ An analogous pattern, although less pronounced, is observed across regions. Figure 2 provides a visual insight on the high concentration of green productions across regions (panel a). Out of 278 NUTS2 regions, only 102 have an average GRP value higher than the mean (0.503). Using a standard locational Gini coefficient, the spatial concentration of green activities is 0.444, compared to a concentration of non-green manufacturing activities of 0.413. In line with the cross-country evidence of Bontadini and Vona (2023), the darkest green regions are observed in Denmark (Midtjylland, Syddanmark and Nordjylland among others) and Germany (Oberpfalz, Mittelfranken and Tübingen among others). In other countries, some green industrial regions are also observed in Austria (Oberösterreich and Steiermark), Spain (País Vasco), Sweden (Småland med öarna and Östra Mellansverige) and Italy (Friuli-Venezia Giulia, Emilia-Romagna and Lombardia, see Table A3 for details).

Finally, green production shocks disproportionately occur in regions that are already green (panel b of Figure 2). The largest increases are indeed observed in Denmark, Austria and Germany, and in a few regions of Spain, France and Poland (See Table A4 for details). The path-dependency in green production is captured by a high and statistically significant correlation between the three-year change in GRP and its initial level (0.311, significant at the 1% level), conditional on year fixed effects. As a result, pre-existing differences in green regional penetration could contaminate the estimated effects of green industrialisation shocks on local employment growth.

3 Empirical strategy

We estimate the local labour-market effects of green-industrialisation shocks using the following specification:

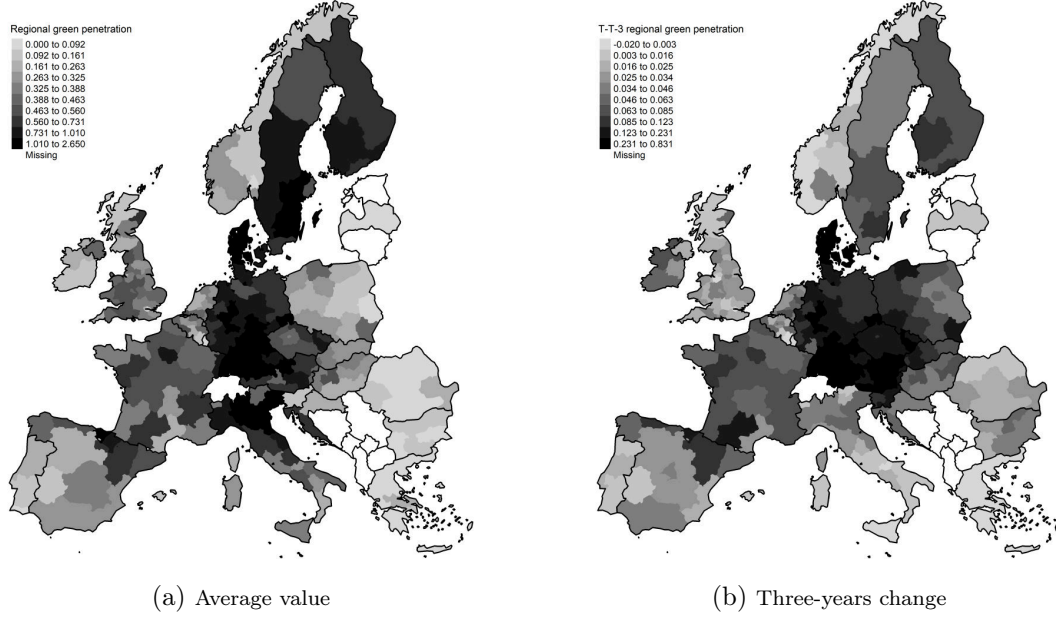
$$\Delta Y_{r,t_k} = \alpha + \beta \Delta GRP_{r,t_k} + \gamma \mathbf{X}'_{r,t_0} \times \tau_t + \tau_t + \eta_c + \epsilon_{r,t}. \quad (3)$$

$\Delta Y_{r,t_k}$ is the change between t and $t - k$ (with $k = 3$ in our favourite specification) in regional employment-to-active-population ratio. $\Delta GRP_{r,t_k}$ is the change in green regional penetration per worker, as defined in Equation 2. $\mathbf{X}'_{r,t_0}$ is a vector of key control variables: (i) the regional share of manufacturing employment, and (ii) the non-green manufacturing penetration.¹⁸ The former accounts

¹⁷Table A2 shows that, at 2-digit NACE level, only 7 sectors out of 24 produce green goods without being identified as polluting. These are: 33 - Repair and installation of machinery and equipment; 26 Manufacture of computer, electronic and optical products; 30 Manufacture of other transport equipment; 27 Manufacture of electrical equipment; 28 Manufacture of machinery and equipment n.e.c.; 16 Manufacture of wood and of products of wood and cork; 29 Manufacture of motor vehicles.

¹⁸Non-green manufacturing penetration is constructed analogously to GRP, with the value of non-green production taken at baseline, the average value between 2000 and 2003)

Figure 2: GRP by NUTS2 region, levels and three years change



Notes. These maps show the average GRP (panel (a)) and its three-year change (panel (b)) by NUTS2 regions in the EU. The average refers to the whole period, from 2003 to 2017. Intervals correspond to deciles. Average values are weighted by the share of the regional population over the EU one.

for the so-called ‘missing share component’ identified as a key confounding factor by the recent literature on shift-share instrumental variable design (Borusyak et al., 2022).¹⁹ The latter accounts for the size of industrial production in the region. In some robustness checks, we expand the set of controls to other potential confounders (see subsection 4.2). These are taken at baseline t_0 (the average value between 2000 and 2003) and interacted with year dummies (τ_t) to allow for non-linear effects of initial conditions on employment dynamics.²⁰ τ_t and η_c are, respectively, time and country dummies that control for global shocks and country-specific linear trends. $\epsilon_{r,t}$ is the error term. To improve the representativeness of our estimates, we weight the regressions using the baseline shares of the regional population over the EU one.

Although Equation 3 includes extensive fixed effects and baseline controls, GRP shocks can hardly be considered as-good-as randomly assigned. First, GRP is subject to measurement error because, within 2-digit NACE sectors, green production is also highly concentrated in a handful of 4-digit sectors (Bontadini and Vona, 2023), for which we cannot observe the employment shares at the NUTS2 level. This measurement error typically results in attenuation bias of the OLS estimates. Second, omitted variable bias is a common issue in analyses where labour market outcomes are regressed on indicators of structural transformations (Autor et al., 2013; Acemoglu and Restrepo, 2020). Specifically to the green transition, regions hosting green production facilities tend to be high-tech and have a solid skill base,

¹⁹Without controlling for the initial degree of industrialisation, sector-specific industrial shocks, such as those used in our work, could mechanically capture differential employment trends for regions at different stages of industrial development.

²⁰We take the controls at baseline to avoid “bad control” problems (Angrist and Pischke, 2009).

and thus are already positioned on robust economic paths (Vona et al., 2019; Popp et al., 2021). At the same time, green investments may be jointly undertaken with automation investments, which reduce labour demand (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Acemoglu and Restrepo, 2022). Because of these intricacies, the direction of the bias from omitted variables is ambiguous.

To isolate plausibly exogenous variation, we build a shift–share instrumental variable that leverages differences in the regional green patent exposure.

$$\Delta IV Gpat_{r,t_k} = \sum_j \frac{L_{rj,t_0}}{L_{cj,t_0}} \times \frac{\Delta Gpat_{cj,t}^{NonEU}}{L_{r,t_0}}. \quad (4)$$

$L_{rj,t_0}/L_{cj,t_0}$, the share component, are the employment shares of manufacturing industry j in region r and country c at time t_0 (avg. between 2000 and 2003). $\Delta Gpat_{cj,t}^{NonEU}$, the shift component, is the change in the stock of EPO green patents by non-EU based inventors between t and t_k allocated to country-sector pair (cj) .²¹ The shift is allocated to a country-sector pair (cj) proportionally to the initial patent stock of that country in this sector over the EU green patent stock at time t_0 (2002). Therefore: $\Delta Gpat_{cj,t}^{NonEU} = (Gpat_{cj,t_0} / \sum_c Gpat_{cj,t_0}) \times \Delta Gpat_{j,t}^{NonEU}$, where $\Delta Gpat_{j,t}^{NonEU}$ is the change in the stock of green patents by non-EU based inventors in sector j . Importantly, employment shares and patent shares play distinct roles in the construction of the instrument. The employment shares $L_{rj,t_0}/L_{cj,t_0}$ represent the exposure shares capturing the extent to which each region is structurally exposed to shocks hitting industry j . By contrast, the patent shares $Gpat_{cj,t_0} / \sum_c Gpat_{cj,t_0}$ act as allocation weights that distribute the global industry-level shock $\Delta Gpat_{j,t}^{NonEU}$ across EU countries.

The intuition behind this instrument is that regions with stronger initial green capabilities are able to benefit relatively more from a global green technology push, akin to shift-share designs that leverage variation in the baseline exposure to new technologies on the workforce (Acemoglu and Restrepo, 2020; Acemoglu et al., 2022).²² The main difference is that here capabilities are measured using patents rather than workforce skills. Our instrument is also in line with models and empirical evidence highlighting path-dependency in green knowledge creation (Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016). In our setup, the use of third-country inventions helps to navigate the trade-off between instrument strength, as implied by path-dependency, and exogeneity.

To give a first insight on the instrument’s relevance, Figure A2 shows the raw correlation between

²¹We take all inventors that do not reside in the EU and further exclude cross-country patents if one of the inventors is based in the EU.

²²For a practical example consider the following. A new patent application related to wind technologies filed by Chinese inventors, the shift, is deemed to positively benefit regions that already have a relative advantage in wind patents, such as Danish ones, through various channels. First, foreign competition typically stimulates domestic inventors closer to the technological frontier, while selecting out those farther away (Acemoglu et al., 2006). Second, it can complement domestic invention if patents result from broad international collaborations, making local producers more productive. Third, even if invention abroad are destructive to local producers, regions with a pre-existing technological advantage are more likely to perform relatively better than regions without it.

the three-year change in the green patent shift-share instrumental variable and the three-year change in GRP. As one could expect, the correlation is quite strong and positive. This result is corroborated by a formal test of the strength of the excluded instrument in the full two-stage least squares model based on Equation 3 (i.e., Kleibergen-Paap F-statistic). Modern treatment of shift-share instrumental variable requires a careful validation of the plausibility of the underlying identifying assumptions (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Subsection 4.1 is dedicated to the discussion and testing of such identifying assumptions, supporting the validity of our empirical strategy.

4 Main results

Table 1 reports the OLS (odd columns) and 2SLS (even columns) estimates of the relationship between regional employment growth in different macro sectors and GRP shocks. Panel A presents results for total, manufacturing and non-manufacturing regional employment, while Panel B focuses on construction, services and agriculture plus mining regional employment.²³ For almost all macro-sectors, our estimates show a positive and highly statistically significant effect of the triennial change in green regional penetration on the three-year change in the employment-to-active population ratio. Estimated coefficients are almost an order of magnitude larger in our favourite 2SLS specification, where technology shocks are used to instrument production shocks. The lower OLS coefficient stems from an attenuation bias due to measurement error, but also reflects stronger employment effects on compliers. That is: a stronger effect on regions where higher green technological capabilities at baseline attract green production shocks.

The estimated coefficients can be interpreted as the effects of a 1'000€ three-year increase in GRP on the employment-to-the active population. However, the median three-year increase in GRP is only 46€ in our data (Table A1), thus the coefficients should be multiplied by 0.046 to obtain a reasonable range of variation. In our favourite 2SLS specification of column 2, a three-year change in GRP implies a change in the employment-to-population share of 0.008 ($0.046 \times \hat{\beta}$). Still, this quantification is inconsistent with an accurate LATE interpretation of the 2SLS coefficients. Indeed, only part of the median three-year increase in GRP is accounted for by exogenous green technology shocks. This part can be quantified using the first-stage coefficient and is equal to 0.007 (7€).²⁴ Using only the three-year change in GRP explained by the instrument, our favourite specification implies an effect of green industrialisation shocks on the share of employment-to-active population of 0.0011, or slightly more

²³Non-manufacturing is the sum of employment in construction, services and utilities. Given its small size and for the sake of space, we do not report here the results related to utilities, but we discuss them in the next sub-sections.

²⁴This number is obtained multiplying the median value of the green patents shift-share instrumental variable (0.0000041) by the first-stage coefficient of the shift-share instrumental variable (1658.106).

Table 1: GRP on regional employment

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.028*** (0.007)	0.166*** (0.038)	0.010*** (0.003)	0.053*** (0.015)	0.022*** (0.008)	0.126*** (0.036)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.007*** (0.002)	0.076*** (0.014)	0.016** (0.007)	0.039 (0.030)	-0.004 (0.007)	-0.013 (0.030)
<i>N</i>	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1658.106***		1658.106***		1658.106***
KP F-Stat		53.4		53.4		53.4
CD F-Stat		79.4		79.4		79.4
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

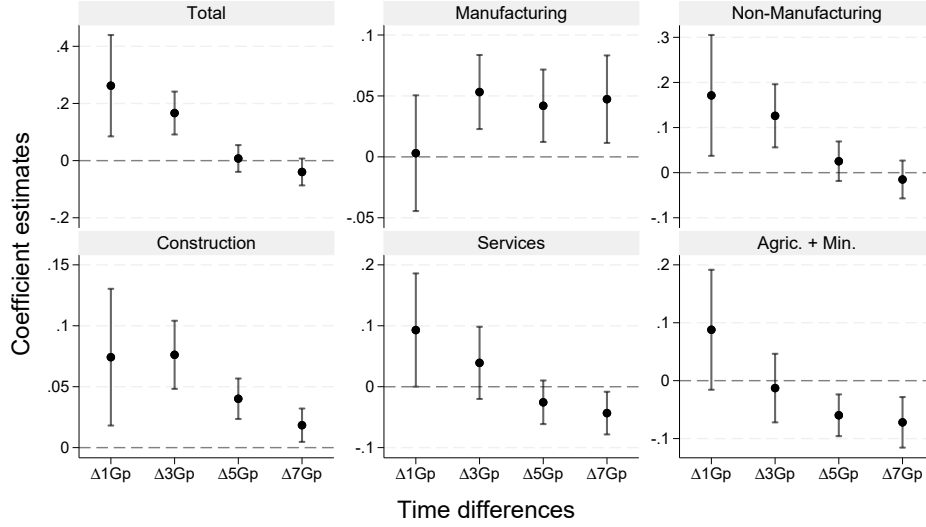
than one tenth of a percentage point. If compared to the median employment-to-active population, this results into an increase of 0.12% ($0.0011/0.923 \times 100$).²⁵

Moving to specific sectors in the rest of Table 1, we observe a similar employment effect in terms of magnitude in both the manufacturing sector, which receives the positive GRP shocks, and the non-manufacturing sector, which benefits indirectly from these shocks through the multiplier effect. Outside manufacturing, we observe additional job creation especially in the construction sector, in line with previous literature (Popp et al., 2021; Fabra et al., 2024; Cappa et al., 2024). We interpret the effect on construction as the additional multiplier effect of infrastructural investments complementary to the green transition. Another interesting result is that the overall effect in column 2 of Panel A is smaller than the sum of the effects in manufacturing (col. 4) and non-manufacturing (col. 6). This is because total employment also includes primary industries (mining and agriculture), for which the estimated effect of GRP is negative and statistically insignificant (Panel B col. 6). This result suggests that GRP accelerates the secular reallocation of labour from primary sectors to manufacturing and

²⁵Note that the bias of the OLS becomes smaller when using this logic for the quantification. Indeed, for the OLS regression, the effect should be quantified using the median three-year change in green regional penetration (0.046), thus the implied change in the employment-to-population is 0.0013.

construction.

Figure 3: 2SLS estimates of GRP on regional employment

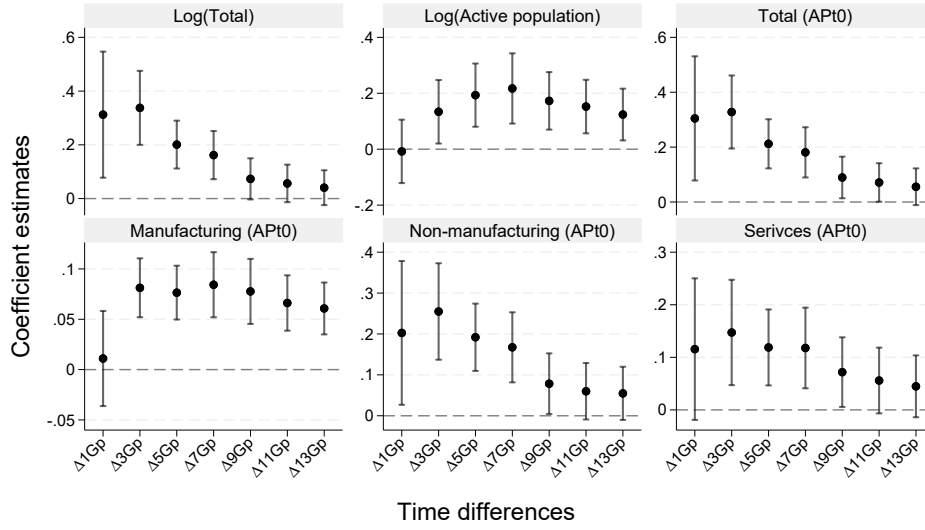


Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five- and seven-year changes. Dependent variables: the k -year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7. CD F-stats: 14.9; 79.4; 174.8; 191.8. 95% confidence intervals.

Next, we explore the time profile of GRP shocks estimating the model of Equation 3 varying the time difference $t - t_k$. Figure 3 plots the main coefficients of the favourite 2SLS specification. Specifically, each sub-plot reports the time-varying coefficients for each of the macro-sectors. For total employment over active population, the effect is at the peak after one-year and then gradually declines to become statistically insignificant at the five-years difference. Not surprisingly, this pattern is driven by the non-manufacturing sector, which represents the bulk of the local employment in most regions. In contrast, we observe a stable job creation effect in manufacturing, implying that a green industrial push may be able to create stable manufacturing jobs in the local economy. Outside manufacturing, the effects on construction employment remain statistically significant up to seven-years, although decreasing in magnitude. On the other hand, services employment effects are more short-lived and achieve statistical significance only at the one-year difference, become insignificant at the three- and five-years differences, and even turns negative at seven-years. Lastly, the effects on primary activities quickly become negative, reinforcing the sectoral reallocation hypothesis.

To shed further light on the time profile of multiplier effects, we decompose the effect of GRP shocks on the numerator (total or sectoral employment) and the denominator (active population) of our dependent variable. While doing so, we extend the inspected time horizon, looking up until thirteen-year changes. Figure 4 shows the outcome related to this exercise. The top-left and top-

Figure 4: 2SLS estimates of GRP on regional employment and active population over a longer time horizon and with decomposition



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variables: the k -year change in log of total employment; log of active population; total, manufacturing, non-manufacturing (utilities, construction, services), services, all with active population fixed at baseline. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2. 95% confidence intervals.

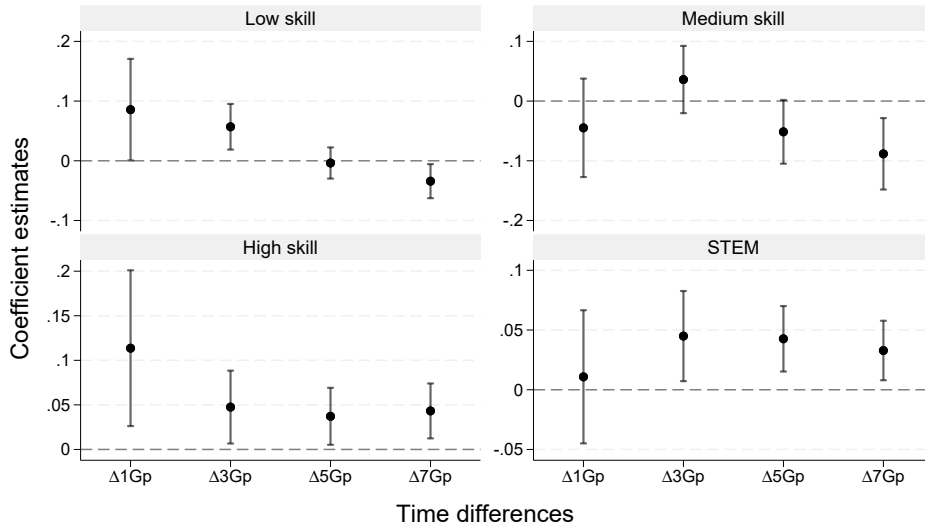
centre figures show that, in the short term, GRP impacts more total employment rather than active population. However, in the long-term the effect of GRP on active population becomes stronger and more persistent, while the one on total employment gradually declines. The former dynamic (i.e., an agglomeration effect) eventually exceeds the latter accounting for the negative seven-year effect on total employment-to active population found in Figure 3. The top-right figure lends further support to this finding, using as dependent variable the change in total employment over an active population fixed at baseline. Quantitatively, the size of the three-year effect on total employment doubles when keeping the active population at baseline. Purging the effect of active-population by sector, the three bottom figures show that the multiplier effects remain positive in the long-term, although vanishing over time in the non-manufacturing and services sectors. Moreover, it is remarkable the stability of the coefficients associated with manufacturing employment, which are consistently positive and significant even after thirteen years. It is worth mentioning that the negative effects on primary activities does not vanish when purging agglomeration effects (Figure A3). This confirms the reallocation hypothesis.

Overall, green industrialisation triggers possible agglomeration effects that increase the population in search of employment and thus the tightness of the local labour market. Net of these induced effects, local job multipliers persist in the long-run, differently from what was found in studies estimating the

local employment effect of renewable energy generation (Fabra et al., 2024; Scheifele and Popp, 2025). This is not surprising as green industrial production is a tradable activity, typically creating supply-side linkages and persistent local spillovers (Moretti, 2010).

Finally, we investigate the quality of the jobs created, using Equation 3 to estimate the skill-biased effect of green industrialisation. The caveat here is that, due to data limitations, we can only measure skills using educational attainments. We look at the effect on low- (lower secondary education and less), middle- (higher secondary education) and high- (tertiary education) skill workers. Given the documented importance of Science, Technology, Engineering and Math (STEM) skills for the green transition (Vona et al., 2018; Popp et al., 2024), we define STEM employees as the number of workers employed in science and technology activities and with tertiary education. Figure 5 and Table A5 in the Appendix align with previous findings in the literature showing a positive and persistent impact of GRP, especially on college graduate and STEM workers. Despite declining over time, the job creation effect is also strong on workers with basic education, which is again consistent with findings of Popp et al. (2021) for the US and the high low-skill intensity of construction jobs. In contrast, we find no significant effect on middle skill workers. Figure A4 confirms these results even when netting out agglomeration effects.

Figure 5: 2SLS estimates of green regional penetration on regional skill level



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five- and seven-year changes. Dependent variables: the k -year change in regional employment over active population by: high-skill (tertiary education); middle-skill (higher secondary education and less); low-skill (lower secondary education and less); STEM (workers employed in science and technology activities and with tertiary education). The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7. CD F-stats: 14.9; 79.4; 174.8; 191.8. 95% confidence intervals.

To summarize, we observe a modest multiplier effect of GRP in the medium-term that gradually

disappears in the long-run. Medium-term multipliers are mostly concentrated in the construction sector. In turn, the service sector positively benefits from short-term multipliers, which then fade away because GRP increases the labour supply and thus the tightness of local labour market. As a long-term pay-off of green industrialisation, more exposed regions remain endowed with a larger base of manufacturing and construction activities, as well as of STEM and college graduate workers.

4.1 Validation of shift-share instrument

In this sub-section, we discuss the identifying assumptions that support our shift-share instrumental variable design. Moreover, we present results that corroborate the validity of this research design.

The credibility of our instrument rests on the exclusion restriction that, conditional on industry-specific and country trends, pre-existing green technological capabilities affect regional employment dynamics only through GRP shocks. Because shift-share instruments are implicitly a linear combination of multiple instruments (Goldsmith-Pinkham et al., 2020), the exogeneity assumption (and the related parallel trend assumption) can be violated both for the whole instrument and for each of the shares used to build it. More specifically, Goldsmith-Pinkham et al. (2020) suggest to decompose the shift-share instrumental variable into a weighted average of just-identified estimates derived from individual instruments. The resulting weights, known as Rotemberg weights, quantify the contribution of each instrument to the overall 2SLS estimate and allow testing for plausible violations of the parallel trend assumption not only for the whole instrument, but also for components identified as more important by the decomposition.

Following Goldsmith-Pinkham et al. (2020), we rely on the identifying assumption that the initial sectoral shares used to assign the green technology shocks to regions are exogenous. In doing so, we begin by showing the top-five industries that, according to the Rotemberg weights (Goldsmith-Pinkham et al., 2020), contribute more to the overall 2SLS coefficient. Table A6 shows that three of the top-five industries are among the highest in terms of green production (28, 27, and 26 - see Table A2), while two only have marginal green production (20 and 29). The top five industries receive more than three quarters of the absolute weight in the estimator (0.771). In particular, the first two (28 and 27) account for about half of it (0.551/1). This is consistent with the high-degree of concentration in green production (Table A2). Table A6 also shows the baseline (avg. 2000-2003) employment share within manufacturing of these sectors and reports examples of green goods that fall within these sectors.

Based on this finding, we assess the plausibility of the parallel trend assumption for the whole shift-share instrumental variable as well as for the top-five sectors identified by the Rotemberg weights. As in Goldsmith-Pinkham et al. (2020), we regress the pre-sample (from 2000 to 2003) dependent variables

in levels either on the green patents-shift-share instrumental variable at t_0 or on one of the 2-digit employment shares of top-five sectors at t_0 , interacted with year fixed effects. To mimic the main specification of Equation 3, we include in these regressions region and year fixed effects, country linear trends, and the previously discussed controls interacted with year fixed effects. We weight estimates by the share of baseline regional population. The reference year is 2000.

Figure A5 shows the results of this empirical exercise. For the aggregate instrument, we detect some signs of positive pre-trends in total employment, particularly in 2002, which may lead to an upward bias in our estimates. However, inspecting the plots for each sector, these pre-trends do not arise in the sector where the shock originates (manufacturing), but are concentrated in the construction sector. Indeed, manufacturing, services and, to a lesser extent, the primary sector all exhibit parallel employment trends before 2003. Inspecting the five sectors with the highest Rotemberg weights further mitigates concerns regarding the violation of the parallel trend assumption. Across the board, most sub-figures show rather flat pre-trends. A few notable exceptions are sectors 20 (Manufacture of chemicals and chemical products, which is only marginally green) and 26 (Manufacture of computer, electronic and optical products), which show negative pre-trends in services employment, possibly leading to a downward bias in our estimates. To be sure that these key sectors do not drive our main results, we further validate our shift-share instrumental variable design by excluding them one-by-one from the instrument and replicating the main analysis accordingly. Tables A7, A8, A9, A10 and A11 reassure us that our main results are not driven by any of these key sectors, as the estimates remain qualitatively in line with the main ones.

We also assess the balance of the aggregate shift-share instrumental variable and each employment share identified by the Rotemberg weights along the two key controls present in the estimating equation: the share of employment in manufacturing and the non-green regional penetration. Specifically, we regress the baseline value of the green patents-shift-share instrumental variable (or of each of the 2-digit manufacturing employment shares of top-5 sectors by Rotemberg weights) on the baseline value of the employment share in manufacturing and the regional non-green manufacturing penetration, including country fixed effects and weighting for the share of regional population over the EU one. Table A12 highlights that both the aggregate shift-share instrumental variable and most shares (excluding 26, 28 and 29) positively correlate with the employment share in manufacturing. On the other hand, only the aggregate shift-share instrumental variable and sector 29 positively correlate with non-green manufacturing penetration. This supports our choice of including these controls non-parametrically in Equation 3.

We further assess the relevance of our instrument by applying the methodology of Lee et al. (2022) to

adjust the t-statistics of the second-stage coefficients.²⁶ Table A13 shows that almost all the coefficients of interest of Table 1 have high enough adjusted t-statistics to preserve statistical significance at the 1% level. The only exception is the one related to non-manufacturing employment, which, however, does so at a 5% level.

Another issue concerns the interpretation of the IV estimates as Late Average Treatment Effects (LATE, Imbens and Angrist, 1994). To interpret shift-share instrumental variable estimates as LATEs, the monotonicity assumption must hold. In our specific case, it requires that the shift-share instrumental variable variable has a positive effect on green production on all the regions. This is not obvious as, for example, a green invention in China could reduce green production in Europe through a business stealing effect. Although this assumption cannot be tested directly, we perform a Monte Carlo simulation where we re-estimate 1,000 times our main coefficient of Table 1 by redrawing regions with repetition and thus implicitly excluding a few regions at the time. We then plot the estimated first-stage coefficients obtained for each sub-sample to detect large deviations from the central value that we estimated for the whole sample. Figure A6 shows that the distribution of the coefficients of the first stage is consistently positive - thus excluding large violations of the monotonicity assumption - and roughly centred around the baseline estimated value of the first-stage coefficient. Overall, these pieces of evidence provide solid support to the credibility of our identification strategy.

4.2 Robustness checks

In this subsection, we assess the robustness of our main estimated effects (Table 1) to different versions of the main specification. These additional results are included in the Appendix for the sake of space.

A possible concern relates to the fact that GRP may partly reflect variation in regional employment structure rather than true differences in green production intensity. To investigate this issue, we replicate the 2SLS analysis at the country-level, where green production is measured without measurement error linked to the allocation of green production to region through the sectoral employment shares.²⁷ Figure A7 reports the results, which remain statistically significant and of similar sign if compared to

²⁶Lee et al. (2022) address the issue of invalid inference in IV estimations caused by weak instruments, challenging the reliance on arbitrary thresholds like $F\text{-stat} > 10$. Lee et al. (2022) introduce the tF procedure, a robust inferential method for instrumental variable regressions that adjusts t-statistics and confidence intervals using the first-stage F-statistic. The resulting procedure usually leads to more demanding t-statistics.

²⁷We formally estimate

$$\Delta Y_{c,t_k} = \alpha + \beta \widehat{\Delta GP}_{c,t_k} + \gamma \mathbf{X}'_{c,t_0} \times \tau_t + \tau_t + \epsilon_{c,t}$$

where $\Delta GP_{c,t_k} = \sum_j \frac{\Delta GP_{cj,t_k}}{L_{c,t_0}^{Manuf.}}$ and the instrumental variable is $\Delta IVGpat_{c,t_k} = \sum_j \frac{\Delta Gpat_{cj,t_k}^{NonEU}}{L_{ct_0}^{Manuf.}}$. We divide changes in green production and in the instrument by baseline employment in manufacturing (avg. 2000-2003) to resemble as closely as possible the regional specification and to compare the magnitudes of the effects. Alternatively, if both variables are divided by total baseline employment, the estimates remain virtually unchanged. Estimates are weighted by each country's population share in the EU.

the regional estimates.²⁸ The magnitude of effects is systematically larger than in the regional analysis. Specifically, using only the three-year change in green production explained by the instrument, as in Table 1, a three-year green production shock increases total employment by roughly one fourth of a percentage point (0.0025) — slightly more than double the corresponding regional estimate. This difference is consistent with the framework of Chodorow-Reich (2020), who shows that regional regressions typically identify partial-equilibrium local effects, while the aggregate effect can be larger due to positive general-equilibrium spillovers and national feedback mechanisms that emerge when the entire economy is affected. In this interpretation, regional estimates provide a lower bound for the aggregate impact. Overall, this exercise reinforces the validity of our main findings and suggests that regional estimates likely understate the total aggregate effect of green industrialisation.

Table 1 does not report the results related to utilities. Despite being a small sector in terms of employment (average 0.7%), the utilities sector contains activities that are linked to green manufacturing, such as the production, transmission and distribution of electricity. We therefore expect positive multipliers of GRP on utilities employment. Figure A8 shows that this is actually the case, with and without possible agglomeration effects. Remarkably, the time profile of the effects is similar to that of manufacturing employment, suggesting that greener regions experience long-term job growth in the utilities sector as well.

Next, we augment our main specification of Equation 3 including a richer set of potential confounders that were identified as important by the related literatures (Autor et al., 2013; Moretti, 2010; Vona et al., 2019; Chodorow-Reich, 2019). More specifically, we include the following variables at baseline: population density, median age, the share of female population, the share of foreign population, and the share of the population with at least secondary and tertiary education. Table A14 shows that the estimated coefficients remain quantitatively in line with the main ones.

Our main specification controls for time-invariant regional characteristics, country-level and broad industry-level trends, but not for pre-existing regional trends unrelated to green industrialisation. To assess whether our results survive the inclusion of such trends, Table A15 replaces the country-level fixed effects either with NUTS1 or NUTS2 fixed effects. In a first-difference model, this demanding specification allows employment to follow a different linear trend in each region, independently on green industrialisation. We find that the estimated coefficients remain statistically significant at conventional level and increase with respect to our favourite specification with country fixed effects.

As discussed before, one source of bias in the OLS estimates is that green investments may be

²⁸The difference in confidence intervals stems from the use of two alternative approaches. Either robust standard errors (black) or wild-clustered-bootstrap standard errors (500 replications - grey). The latter are the most conservative and necessary given the number of clusters (28).

carried out jointly with automation investments that reduce labour demand (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Hence, controlling for automation investment in our main specification can help avoid a potential source of omitted variable bias. To do so, we measure the exposure to automation at the regional level as in Anelli et al. (2021) and include it as a control variable.²⁹ Table A16 shows that the main estimates are robust to the inclusion of this control whose related estimates, as expected, are negatively associated with employment growth.

Next, we change the level of clustering of the standard errors from NUTS2 to NUTS1. This accounts for possibly larger interdependencies between local labour markets (Manning and Petrongolo, 2017). Table A18 shows that the significance level of the GRP coefficients remains within accepted ranges, except for the construction sector.

Lastly, we assess the sensibility of our estimates to the possible presence of outliers in GRP and in each outcomes inspected. Specifically, we exclude regions where the values of the three-year change in either GRP or each of the outcomes are higher (lower) than the top (bottom) 1%. Table A19 shows that estimates remain virtually the same, achieving at times higher statistical significance. Alternatively, we exclude regions with population density at baseline below the bottom 1%. Table A20 shows that estimates survive this robustness as well.

5 Extensions

This final section extends our analysis into two policy-relevant directions. First, we concentrate on large shocks in GRP that more closely resemble the case of a sudden push in green industrial policy. Second, we assess the effect of GRP in regions that are specialized in pollution-intensive activities and thus may also experience substantial job losses from the green transition.

5.1 Large shocks to green manufacturing penetration

While our data show an upward trend in green productions, higher than the trend in non-green ones (Figure 1), the green industrialisation expansion studied so far cannot be considered a “big push” (Rosenstein-Rodan, 1943; Murphy et al., 1989). Indeed, our study spans a historical period where EU countries lost their initial comparative advantage in some key green products, notably solar PV. In this context, creating local jobs out of green activities may be easier due to the absence of general equilibrium effects associated, for instance, to the increased tightness of local labour markets, especially

²⁹It is worth mentioning that there is no perfect overlap of NUTS2 regions between the main data and the automation exposure one. See Appendix B for details. For consistency, we re-estimate the main results restricting the sample to those NUTS2 regions for which we have automation data and show it in Table A17. Estimates are in line with the main ones.

for workers with green-specific skills.

Taking stock from the related paper of Aghion et al. (2023) on the local labour market effect of automation in France, we mimic the effect of a big green push in a staggered difference-in-difference (DiD) design, where the treatment is a large positive shock to the local green economy. More formally, we estimate the following two-way fixed effects model.

$$Y_{r,t} = \alpha + \sum_{p=-5}^7 \beta_p \mathbb{1}[\Delta GRP > p90]_{r,t}^p + \gamma \mathbf{X}'_{rt_0} \times \tau_t + \tau_t + \eta_r + \sigma_c \times year + \epsilon_{r,t}, \quad (5)$$

where $Y_{r,t}$ and $\mathbf{X}'_{rt_0} \times \tau_t$ are, respectively, one of the outcome variables and of the controls already discussed in Equation 3. τ_t and η_r are year and region fixed effects, and $\epsilon_{r,t}$ is the error term. We include country linear trends, $\sigma_c \times year$, so that this specification is comparable to the 2SLS first-difference specification (Equation 3).

$\mathbb{1}[\Delta GRP > p90]_{r,t}^p$ is a dummy variable equal to 1 for treated regions, defined as regions r experiencing an increase in GRP between t and $t - 1$ above the 90th percentile. We assume that, once a region experiences such a shock, is treated thereafter and we exclude always treated units (Callaway and Sant'Anna, 2021). As in a DiD event study design, the effect of the treatment is decomposed into a series of leads (up to five years) and lags (up to seven years) relative to the region's year of exposure.³⁰ Figure A9 provides a sense of the staggered design, showing the fraction of treated regions by cohort. Around 2/3 of large GRP shocks are observed between 2006 and 2008, before Chinese competition in green production deteriorates the pre-existing EU advantage.

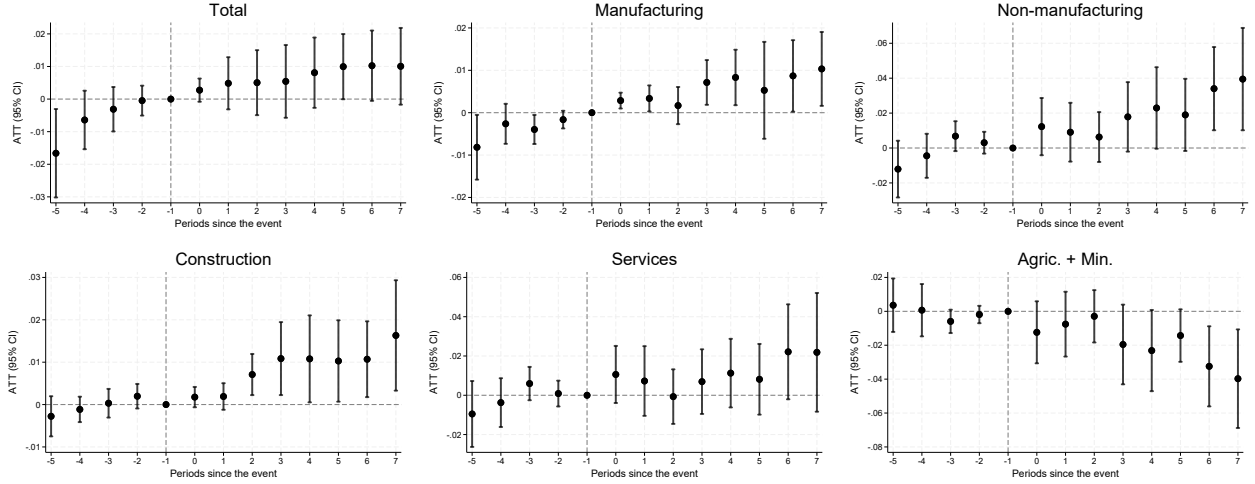
Importantly, this staggered DiD approach does not rely on the technologically-driven source of identifying variation of the shift-share instrumental variable, and hence does not need to be interpreted as a LATE. Assuming that large shocks to GRP are plausibly exogenous, a DiD set-up can be interpreted as an Average Treatment effects on the Treated (ATT). The plausibility of the ATT interpretation rests on the assumption of conditional parallel trends, that can be indirectly tested in an event study design.

Recent DiD literature has shown that, within a staggered design, the two-way fixed effects (TWFE) models may not yield a transparent weighted average of treatment effects when these effects are heterogeneous (see Roth et al. (2023) for an excellent review). To account for this issue, we choose the regression adjustment framework proposed by Callaway and Sant'Anna (2021) (henceforth CS), where the outcome variable is depurated by the controls included in the main specification of Equation 3. As an additional advantage, the CS estimator relaxes the assumption of treatment homogeneity and

³⁰Note that, since our sample starts in 2003 and we define treatment based on shocks in GRP between t and $t - 1$, the first non-missing year in the estimating sample is 2004.

thus allows to estimate group-time ATTs, with groups determined by the initial treatment time of each unit, before aggregating the results. In the main results, we use never-treated regions as the control group, but augmenting the control group with not-yet-treated regions does not substantially affect our results (Figure A10).

Figure 6: Event study estimates of large shocks to GRP

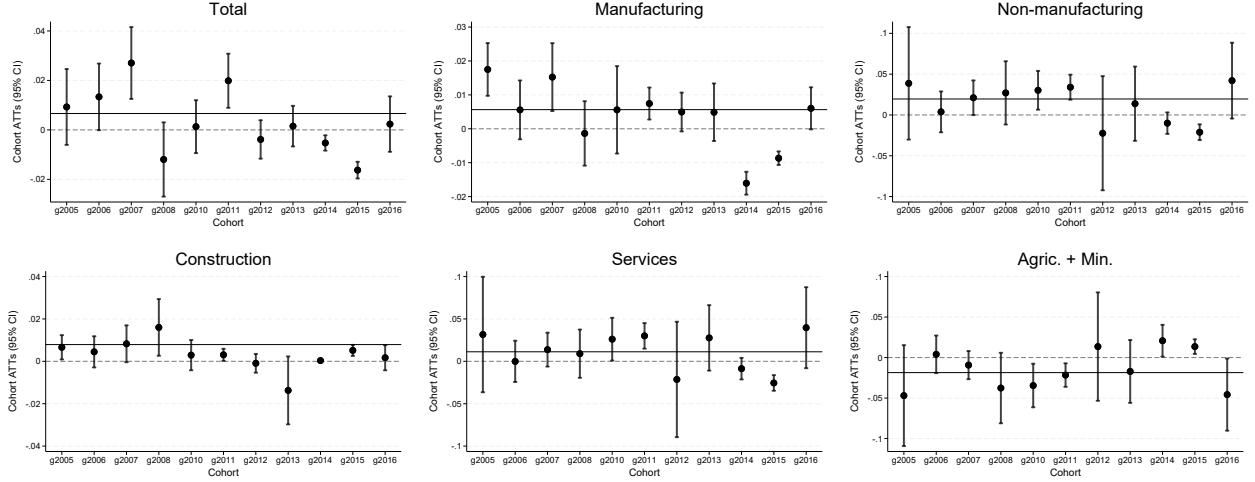


Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant’Anna (2021). Dependent variables: the regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

We display the results of our favourite CS estimator in Figure 6. The results are qualitatively in line with those of the main specification, but the effects are as expected larger, slower to emerge and more persistent also outside manufacturing. More specifically, the coefficients become statistically significant only after five-years, pointing to increases the total employment-to active population ratio by 1.1 pp (0.01/0.092) - an effect ten times larger than the LATE one. Moreover, we do not observe a decline in the employment-to-active population in the services sector and, netting out the agglomeration effect as in Section 4, we find clearer long-term statistically significant effects on all sectors (Figure A11). Reassuringly, most of the sub-plots show no signs of the presence of pre-trends or, for total employment, a negative pre-trend for regions receiving large GRP shocks, making us confident that violations of the conditional parallel trends assumption are not severe in our setup. Both the TWFE and CS estimators show somewhat similar patterns (Figure A12), consistent with the fact that negative weights account for a small fraction of the total ATTs in our case (Table A21). Lastly, Figures A13 and A14 show the results on employment by skill, confirming the patterns previously described.

Further, exploiting the properties of the CS estimator, we decompose the ATT into cohort-specific ATTs. Figure 7 reveals that the earliest-treated groups mostly exhibit positive ATT, driving the bulk

Figure 7: Cohort-specific ATTs of large shocks to GRP



Notes. These figures show the ATT by cohort resulting from estimating Equation 5 with a regression adjustment estimator within the Callaway and Sant’Anna (2021) framework. Cohorts are identified by the year of exposure to treatment. Dependent variables: the regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. The solid black line represents the aggregate ATT. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

of the aggregate impact.³¹ In contrast, later-treated cohorts display more volatile ATTs: some still show positive ATT estimates, while others show estimates that hover around zero or even negative. This evidence suggests that it may be more difficult to reconcile future efforts to promote green industrialisation with job creation. This evidence also aligns with the gradual loss of EU’s advantage in green products and with the fact that most recent green technologies are becoming more labour-saving (Saussay et al., 2025).

5.2 Evaluating the impacts on vulnerable regions

One of the main goals of the EU green deal is to achieve a so-called “just transition”. That is: the policy-driven green transition must not exacerbate regional inequalities, especially by hampering regions more dependent on polluting industries. Place-based policies for left-behind regions are usually advocated by economists on the ground of their high labour supply elasticity (Bartik et al., 2019; Austin et al., 2018). Regions hosting polluting industries and coal mines can be a good target for such policies as they are usually poorer and already on a declining trajectory (Weber, 2020; Vona, 2023; Hanson, 2023). Recent political-economy research suggests that providing opportunities in the green economy to communities that depend on polluting industries helps mitigate their opposition to the green transition (Bergquist et al., 2020; Bolet et al., 2024; Cavallotti et al., 2025).

Inspired by these considerations, we construct a measure of the potential disadvantages created by the green transition which relies on the degree of specialization in polluting industries at baseline

³¹Figure A15 shows clearer patterns net of agglomeration.

(2000-2003). More specifically, we measure brown exposure as the ratio between regional employment in polluting industries and the total regional employment: $BP_{r,t_0} = \sum_j \frac{L_{r,j=poll,t_0}}{L_{r,t_0}}$.³² The average value of BP_{r,t_0} is 0.044, signalling that the average share of employment in polluting industries is rather small (see Table A1). We measure elevated brown penetration by identifying those NUTS2 regions that have BP_{r,t_0} above the 75th percentile.

Figure A16 shows NUTS2 regions by brown exposure (a) and outlines those identified as having a high degree of brown exposure (b). Notable clusters emerge in the West of France, North of Italy and Czech Republic. Table A22 shows balancing tests between brown and non-brown NUTS2 regions. Brown-specialized regions tend to have lower population density, slightly higher median age, and a higher (lower) share of low (high) skill workers. They also have higher employment in manufacturing and non-green regional penetration at baseline, while they do not show differences in terms of three-year changes in green regional penetration and regional green patents exposure. Lastly, and somehow unexpectedly, brown-specialized regions have a higher probability of being exposed to large shocks to GRP.

Econometrically, we assess the differential effect of GRP on brown regions by adding the interaction between the high-brown exposure dummy variable and the three years change in GRP to our main specification of Equation 3. Table 2 shows the results of this empirical exercise, where almost none of the interaction coefficients are statistically significant. Specifically, the effect of GRP on total employment growth is slightly lower in brown specialized regions, but the coefficient associated to the interaction term is far from being statistically significant. The only exception to this pattern is the more pronounced negative reallocation effect of GRP in brown regions on agriculture and mining employment.

When restricting the sample to brown-exposed regions and expanding to other time differences (Figure A17), estimates are in line with the main sample although job creation effects on manufacturing are less precisely estimated (Figure 3). However, netting out agglomeration effects makes the estimated coefficients statistically significant also for brown regions (Figure A18 and Figure A19 — except in the very long-term (after nine-years)).³³ The result that brown-exposed and non-brown exposed regions equally benefit from GRP shocks is confirmed using the DiD-large shock specification (see Figure A20), where we estimate the ATT separately for the two groups of regions against the common control

³²In line with Bontadini and Vona (2023) and the literature cited there, the polluting industries are: 24 - manufacture of basic metals; 25 - manufacture of fabricated metal products; 21 - manufacture of basic pharmaceutical products; 20 - manufacture of chemicals and chemical products; 23 - manufacture of other non-metallic mineral products; 19 - manufacture of coke and refined petroleum products and the entire mining sector (i.e., sectors from 05 to 08, excluding sector 09 which pertains services related to the mining sector).

³³In particular, the fact that estimates are statistically significant in Figure A18 and in Figure A17 implies that the null result of the interaction term in Table 2 is not due to noise.

Table 2: GRP and brown specialization interaction on regional employment

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.023*** (0.007)	0.211*** (0.066)	0.007** (0.003)	0.044** (0.021)	0.022** (0.009)	0.067 (0.079)
* $BP SPEC_{r,t0}$	0.019 (0.012)	-0.046 (0.087)	0.010*** (0.003)	0.011 (0.025)	0.000 (0.012)	0.094 (0.106)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.006*** (0.002)	0.069** (0.030)	0.017** (0.008)	-0.011 (0.065)	-0.006 (0.008)	0.100 (0.070)
* $BP SPEC_{r,t0}$	0.004 (0.005)	0.015 (0.044)	-0.003 (0.008)	0.076 (0.074)	0.008 (0.008)	-0.151** (0.070)
<i>N</i>	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
KP F-Stat		11.1		11.1		11.1
CD F-Stat		16.6		16.6		16.6
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. The endogenous and instrumental variable are interacted with a dummy variable equal to 1 if a NUTS2 has a value of brown exposure higher than the 75th percentile at baseline (avg. 2000-2003). Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

group of never treated. In brown-exposed regions, although the ATTs are estimated less precisely due to a decrease in sample size, a weaker effect in manufacturing is offset by a stronger effect outside manufacturing.

The main policy implication of these results is that brown exposed regions can still benefit from the green industrialisation. Large job creation effects outside manufacturing can be accounted for by the larger labour supply elasticity of more vulnerable regions (Austin et al., 2018). This result is also in line with evidence that green and brown activities utilize a similar set of skills (Vona et al., 2018; Saussay et al., 2022)

6 Conclusions

This paper offers new insights on the effects of green industrialisation on local labour markets in EU countries. While previous work focused on green energy (Fabra et al., 2024; Chan and Zhou, 2024; Cappa et al., 2024; Scheifele and Popp, 2025) or on green fiscal policies (Popp et al., 2021; Wald et al., 2024), we are, to the best of our knowledge, the first to estimate the local multiplier effect of green industrialisation. Within a causal empirical framework, we show that GRP creates jobs in the local economy and the effect is more persistent than those estimated for renewable energy generation. Importantly, we show that the effect is less likely to be affected by pre-existing trends, which were an issue in the related study of Popp et al. (2021).

The aggregate effect on the employment-to-active population masks various structural changes in the local economy. First, we observe a strong and persistent effect on manufacturing employment. Green manufacturing production also increases the share of STEM workers in the local labour market, enhancing the general attractiveness of greener regions. Second, the multiplier effect outside manufacturing is more evident and persistent on construction and utilities, while it is short-lived in the services sector. This finding underscores the crucial role of infrastructure investments for the green transition. Third, green industrialisation accelerates labour reallocation away from the primary sector and triggers agglomeration forces that increase the tightness of local labour markets. Both reallocation and agglomeration effects are in line with the fact that greener regions become more attractive locations to live and work. Fourth, we observe a skill-bias of green industrial activities in favour of high- (especially STEM) and low-skilled workers, which aligns with previous research (Marin and Vona, 2019; Vona et al., 2018). The change in the skill composition is partly driven by induced changes in the local industrial structure. On the one hand, green industries are high- to medium-tech and thus their expansion increases the demand for STEM workers. On the other hand, the expansion of construction allows the absorption of workers laid off from the primary sector and the inflow of new workers.

Although we do not exploit specific green policies to identify local labour market effects, our findings can be used to improve the design of green industrial policies. In particular, the two main extensions of our analysis provide further insights for policy makers. On the positive side, our results suggest that green industrialisation can be a promising part of place-based policies for left-behind brown regions. On the negative side, large green industrialisation shocks are less frequent in recent years and, when they occur, create less jobs. This implies that green subsidies, possibly combined with local content requirements, may be less likely to be effective in creating local jobs in the future. What remains unclear is whether a lower effectiveness is due to the lack of competitiveness of EU countries in

green industries or to the fact that green technologies are becoming more labour-saving. These issues certainly deserve further research.

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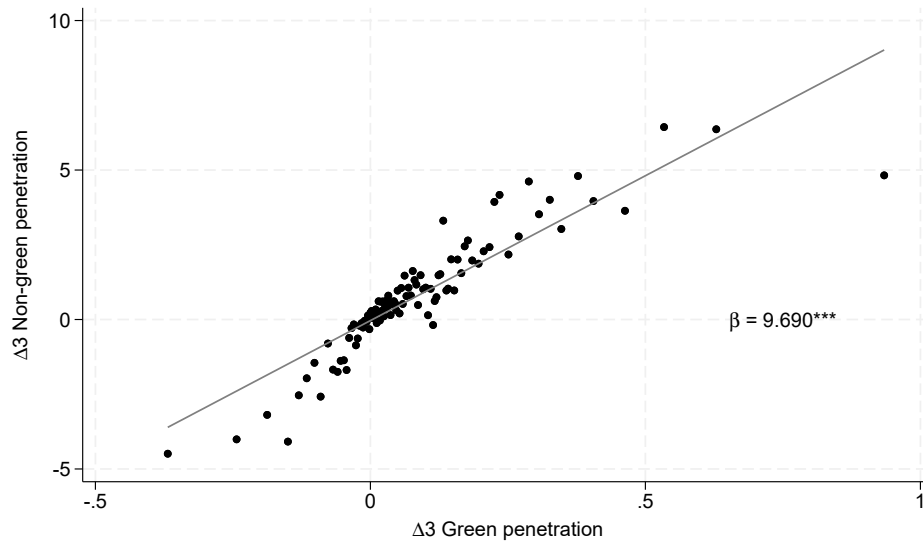
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A Main Appendix

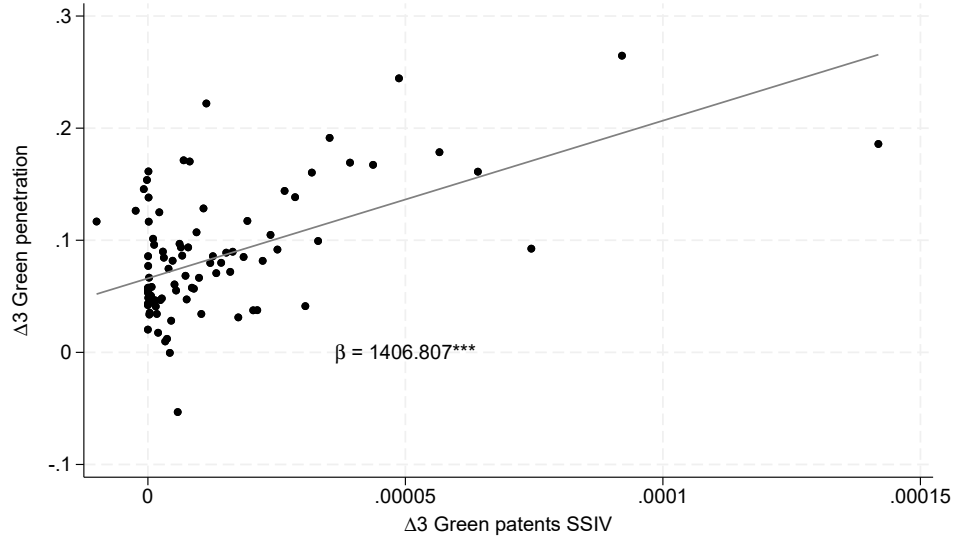
A.1 Figures

Figure A1: GRP and NGRP

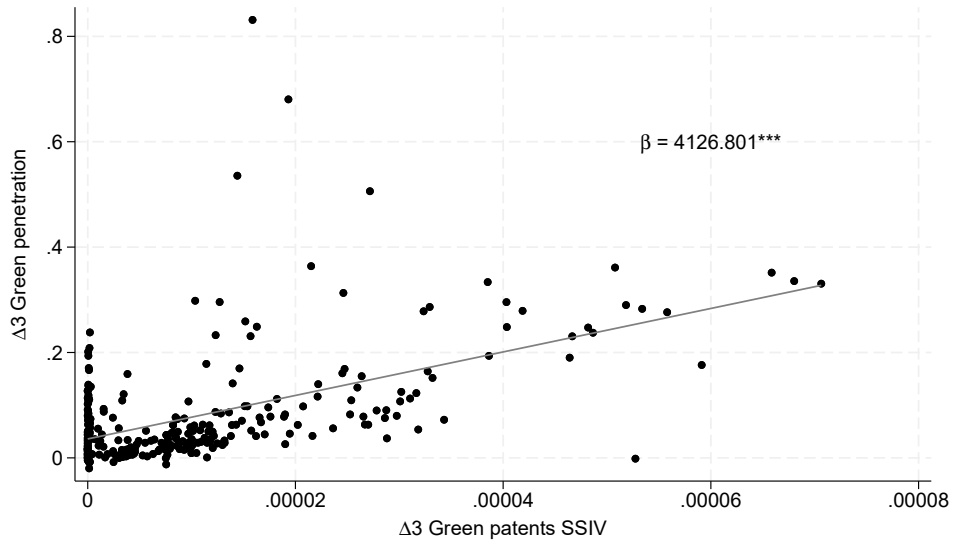


Notes. This graph shows the raw correlation between the average three-year change in regional non-green penetration and the average three-year change in GRP. We weight the two variables by the share of regional population over the EU one. Dots are binned ($n = 100$).

Figure A2: First stage correlation



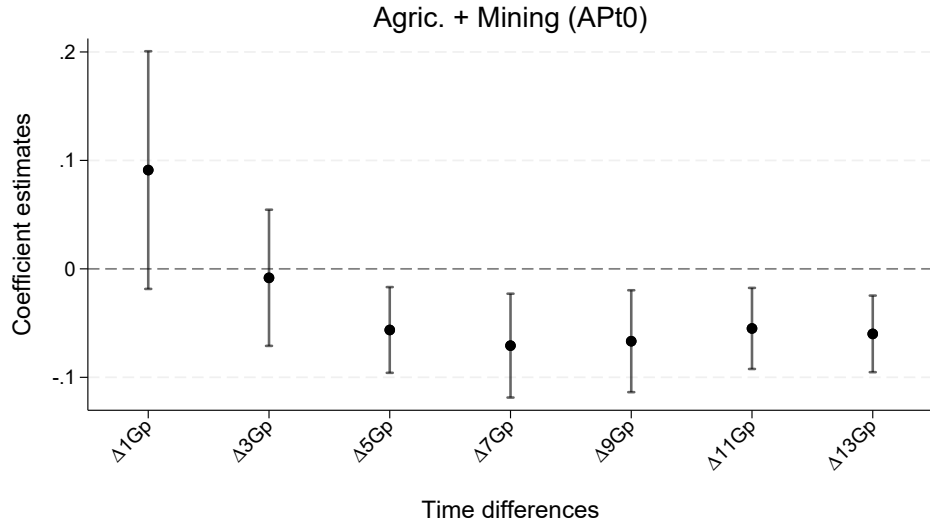
(a) Binned ($n = 100$)



(b) Unbinned (dots = regions)

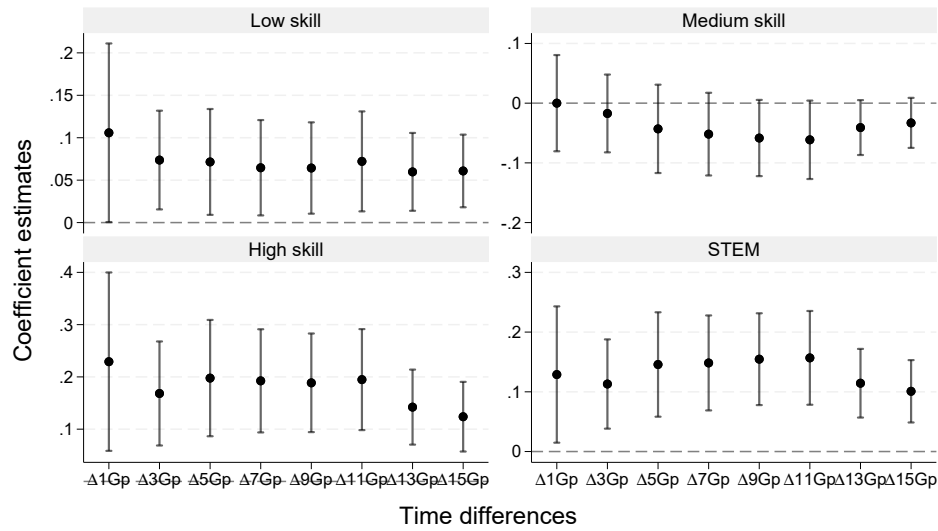
Notes. These panels show the raw correlation between the average three-year change in GRP and the average three-year change in the green patents shift-share instrumental variable. Panel (a) bins the dots across regions and years, with $n = 100$, while panel (b) compute the average of both measures across years, implying that each dot correspond to a NUTS2 region. We weight the correlation by the share of regional population over the EU one.

Figure A3: 2SLS estimates of GRP on regional primary-employment and active population over a longer time horizon and fixed active population



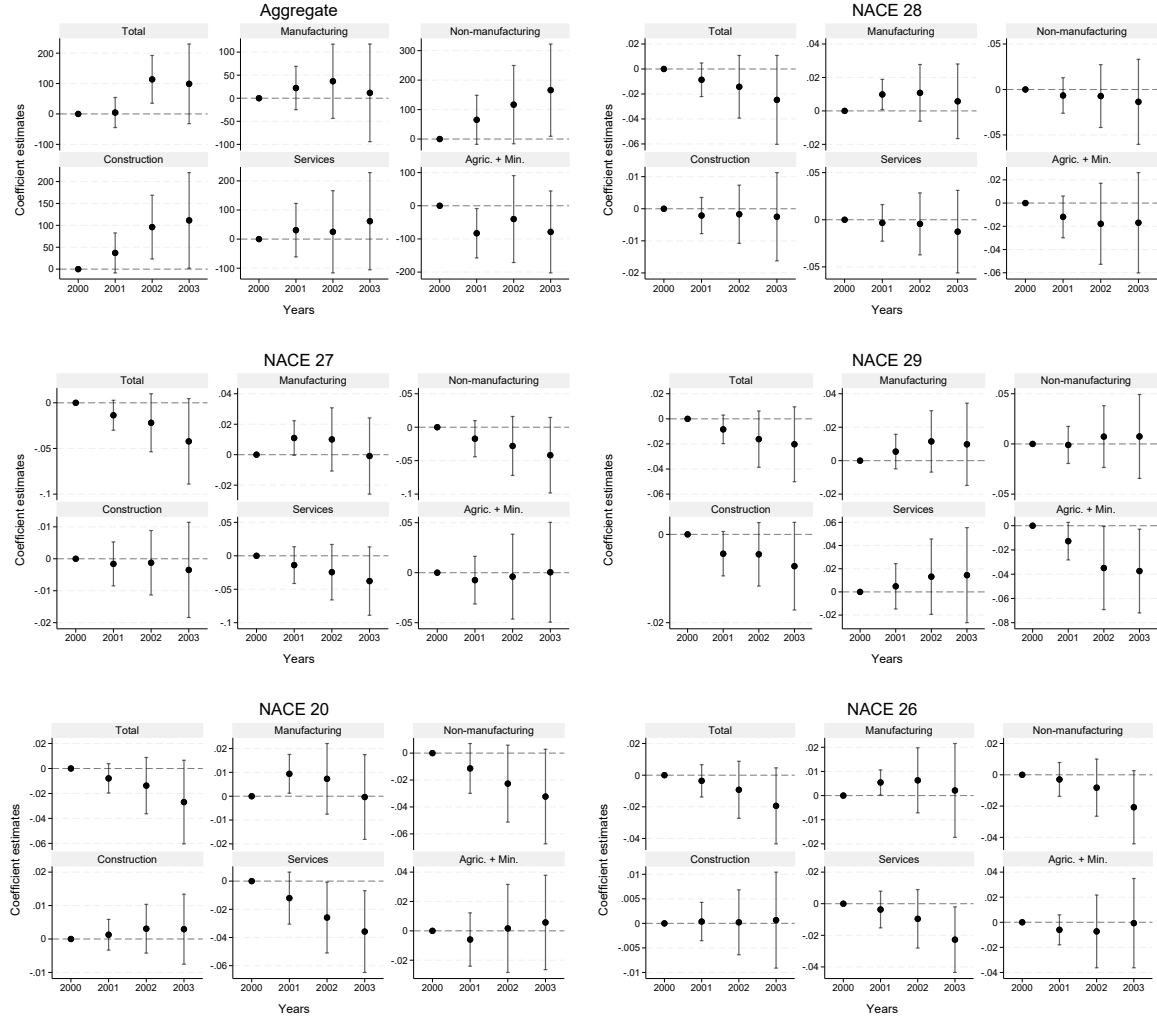
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variables: the k -year change in regional employment in agriculture and mining, with active population fixed at baseline. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2. 95% confidence intervals.

Figure A4: 2SLS estimates of GRP on regional skill level over a longer time horizon and fixed active population



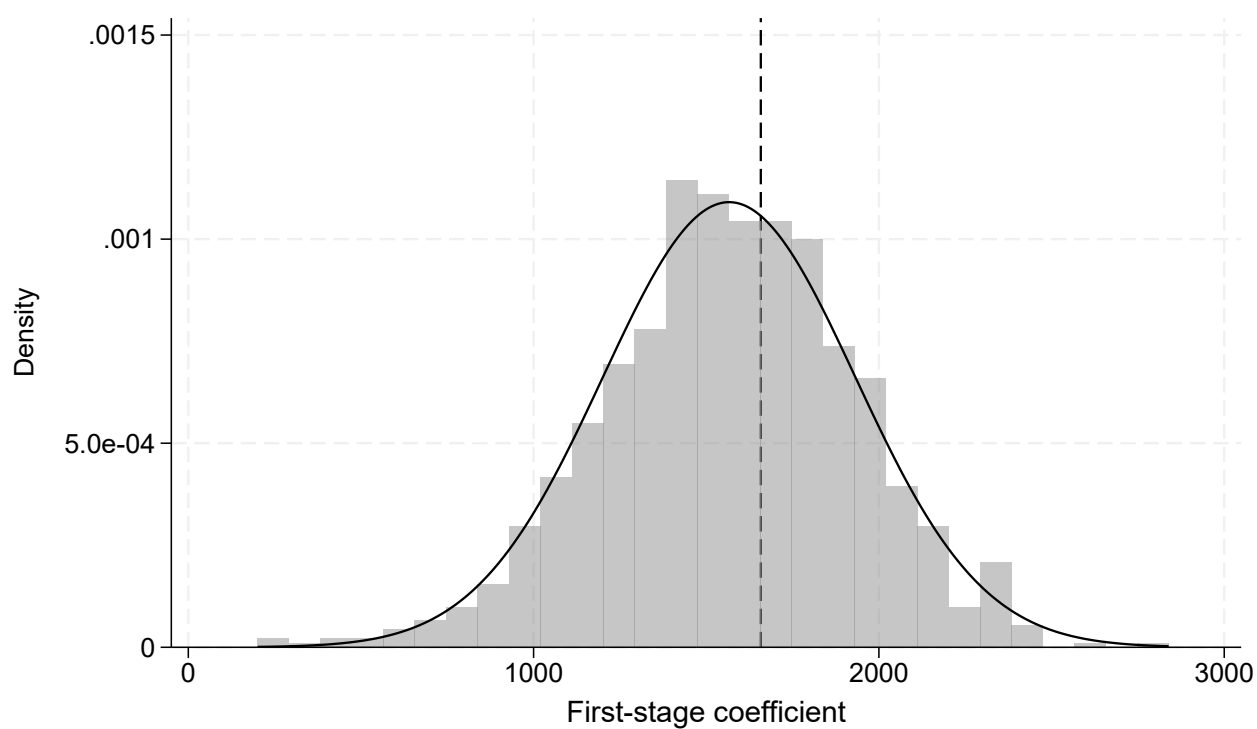
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variables: the k-year change in regional employment over active population by: high-skill (tertiary education); middle-skill (higher secondary education); low-skill (lower secondary education and less); STEM (workers employed in science and technology activities and with tertiary education). In all plots with APt_0 , active population is fixed at baseline. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2. 95% confidence intervals.

Figure A5: Parallel trends of the green patents shift-share instrumental variable by industry share



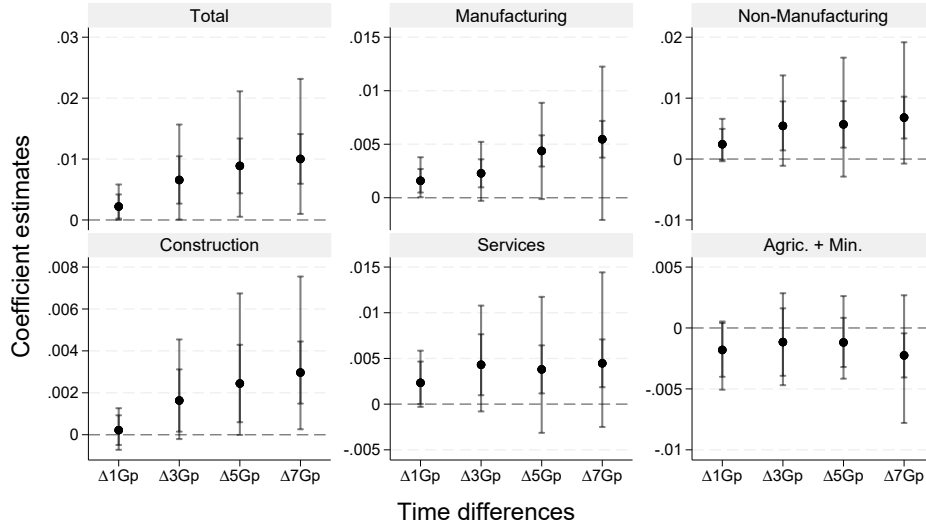
Notes. These figures assess the parallel trend assumption by regressing the green patents-shift-share instrumental variable and each top five Rotemberg weight employment share interacted with year fixed effects on outcomes in levels in the pre-sample period, that is from 2000 to 2003. The reference year is 2000. Regressions include employment share in manufacturing and non-green manufacturing penetration at baseline interacted with year fixed effects, as well as region and year fixed effects and country linear trends. We weight estimates by the share of regional population over the EU one. 95% confidence intervals.

Figure A6: Distribution of the first stage's coefficients, Monte Carlo simulation



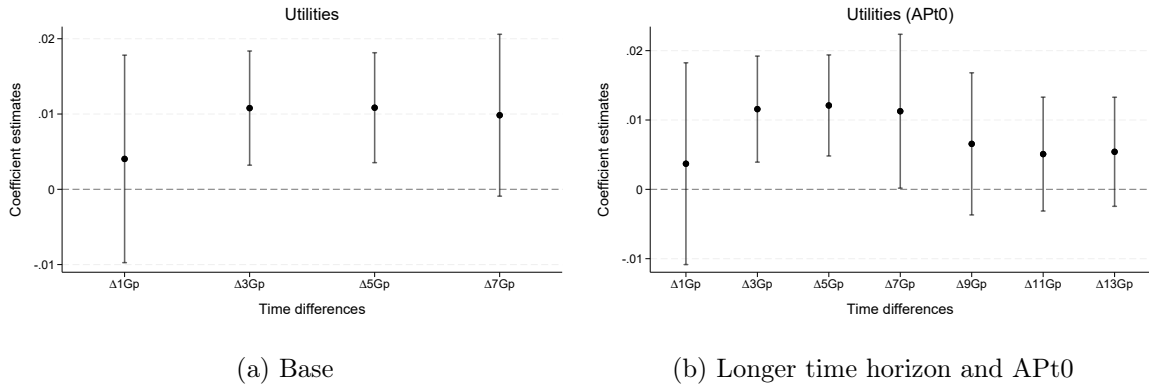
Notes. This figure shows the distribution of the coefficient of the first stage drawn from 1000 different subsamples. The vertical dashed black line correspond to the first-stage coefficient of Table 1.

Figure A7: 2SLS estimates of green production on country employment



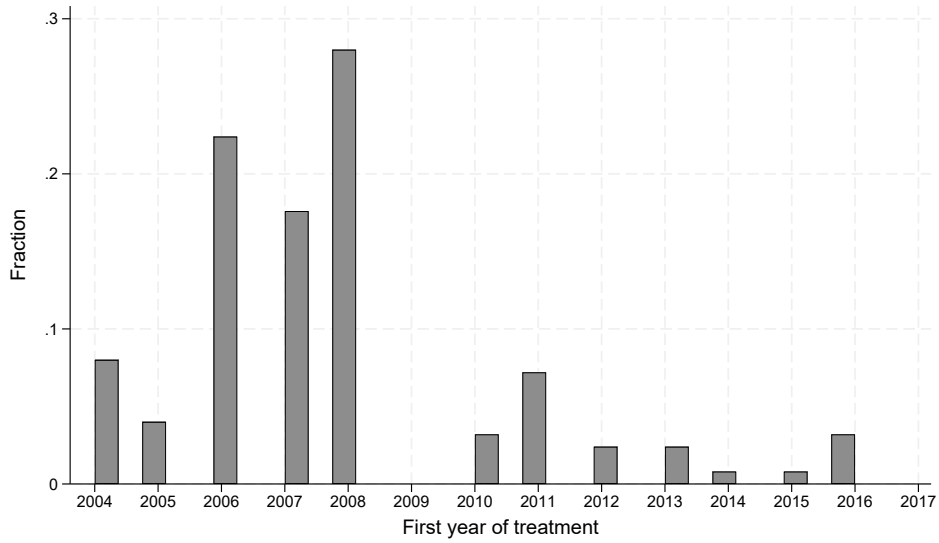
Notes. These graphs replicate the 2SLS estimation based on Equation 3 and on Equation 4 by aggregating the unit of analysis from regional to country. They look at one-, three-, five- and seven-year changes. Dependent variables: the k -year change in country employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GP_{c,t_k}$, refers to the change in the green production in country c between t and $t-t_k$, over country c manufacturing employment at baseline (avg. 2000-2003). The instrumental variable refers to the shift in green-patents from Non-EU countries, allocated to EU countries via their initial stock of green patents, divided by country c manufacturing employment at baseline. Controls include the share of country employment in manufacturing and the country non-green production, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include year fixed effects. Estimates are weighted by the share of country population over the EU one, at baseline. Black confidence intervals refer to robust standard errors. Gray confidence intervals refer to wild-clustered-bootstrap standard errors (500 replications). Number of countries: 28. KP F-stats: 125.6; 163.8; 122.4; 116.1. CD F-stats: 5915.2; 5387.8; 4604.6; 4290.4. 95% confidence intervals.

Figure A8: 2SLS estimates of GRP on regional utilities employment by time differences with and without fixed active population



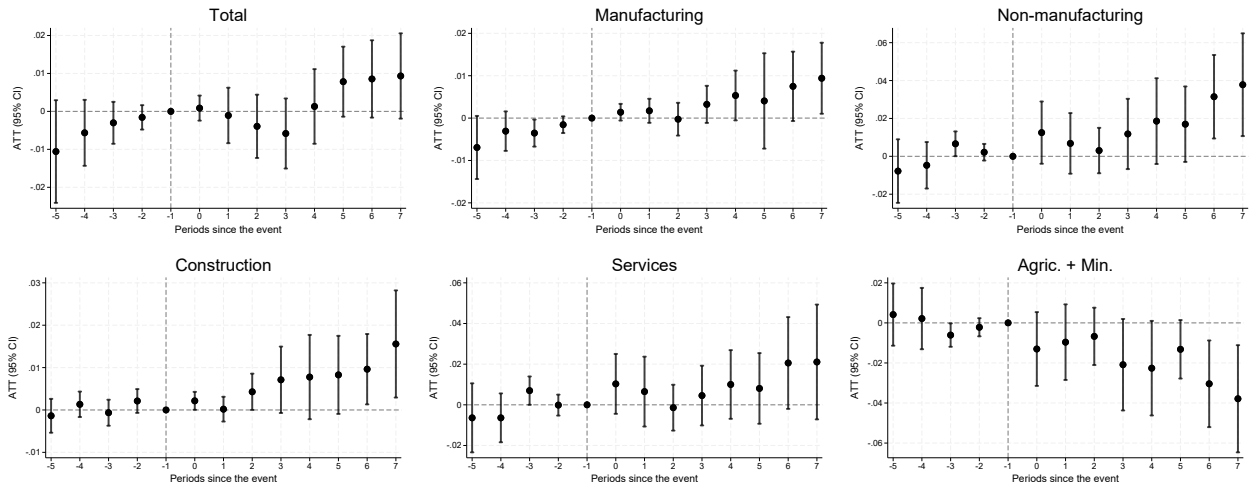
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variable: the k -year change in regional employment in utilities, with varying active population (panel a) and fixed at baseline (panel b). The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 278. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2. 95% confidence intervals.

Figure A9: Large shocks to GRP by first year of treatment



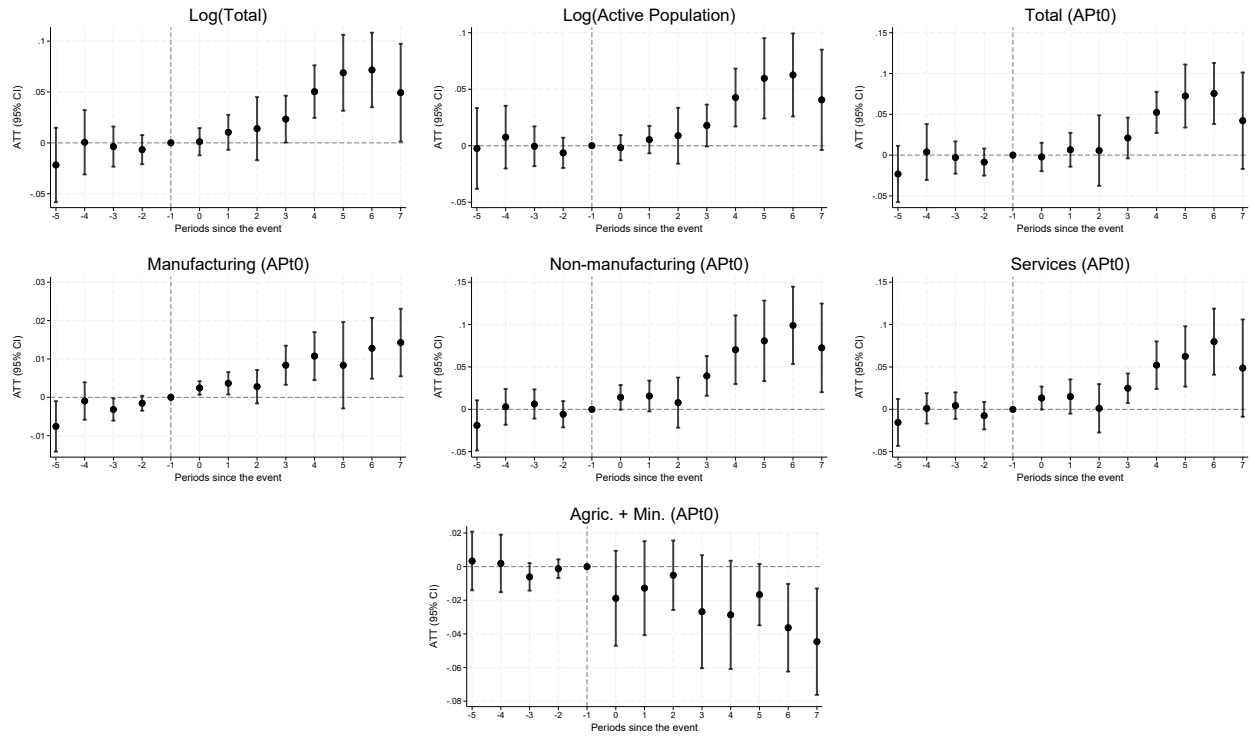
Notes. This figure shows the fraction of NUTS2 regions that are treated over the total number by year, according to estimation strategy Equation 5.

Figure A10: Event study estimates of large shocks to GRP and adding not-yet treated units to the control group



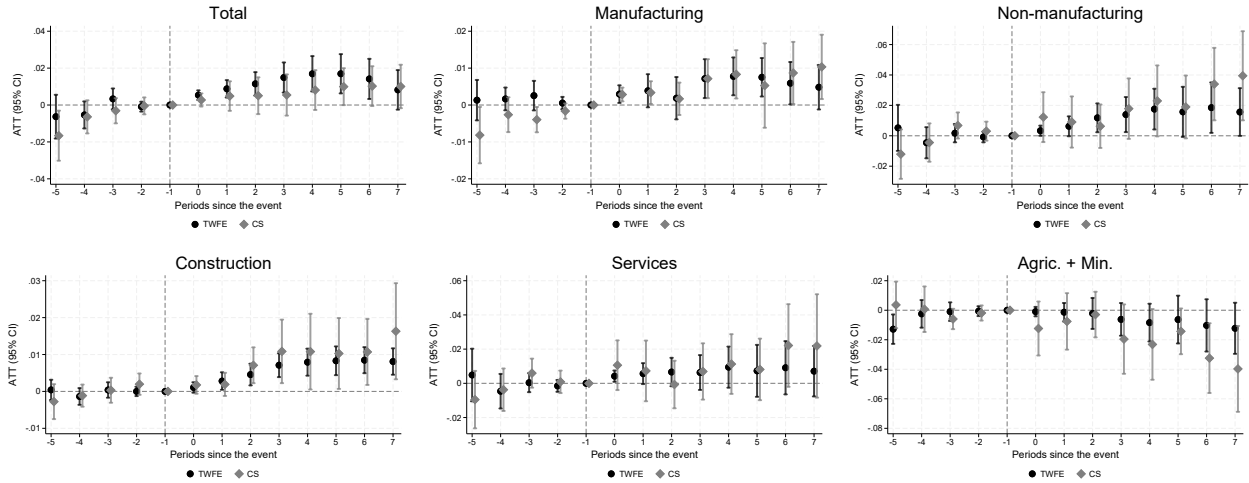
Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant'Anna (2021). Dependent variables: the regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. The control group is augmented by including not-yet-treated regions. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A11: Event study estimates of large shocks to GRP with active population fixed



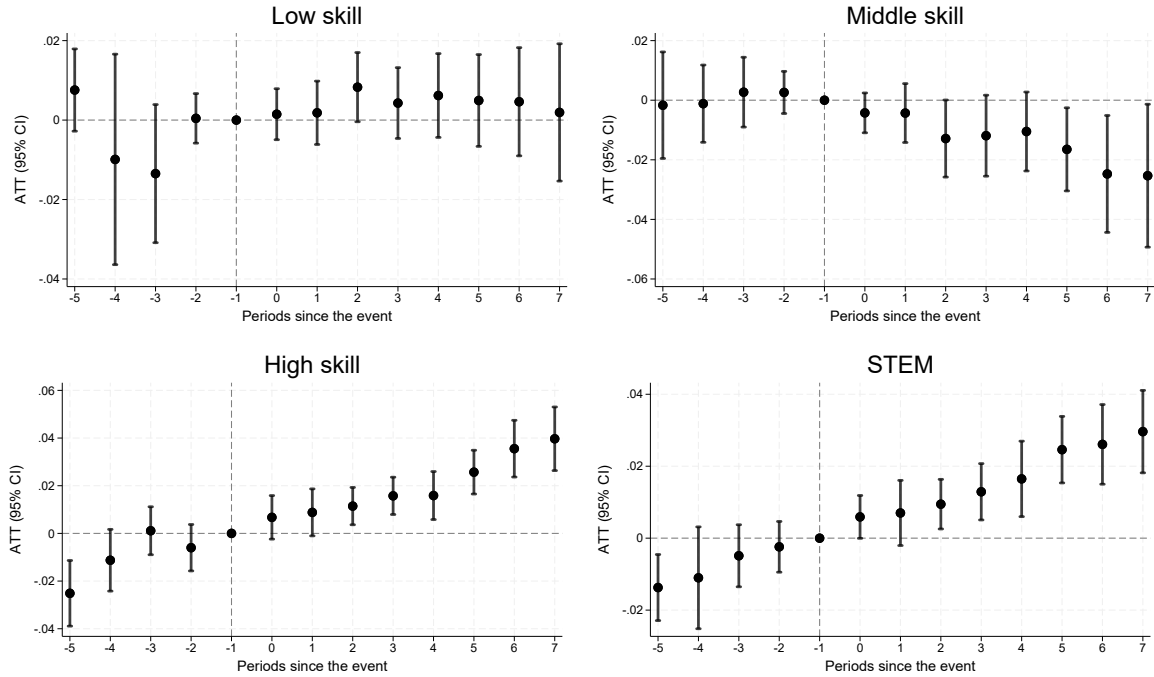
Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant'Anna (2021). Dependent variables: log of total employment; log of active population; total, manufacturing, non-manufacturing (utilities, construction, services), services and agriculture + mining. In all plots with APt0, active population is fixed at baseline. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A12: Event study estimates of large shocks to GRP, comparing TWFE and Callaway and Sant'Anna (2021)' regression adjustment estimators



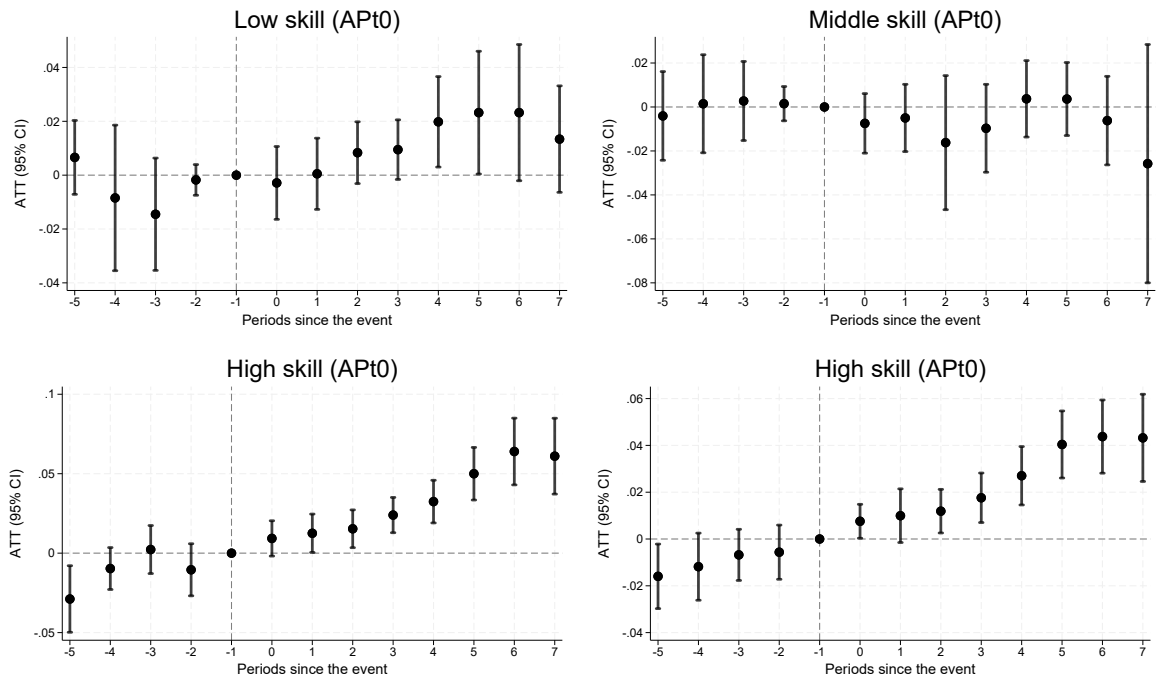
Notes. These plots show the results of the event study specification of Equation 5. They employ TWFE (black circles) and a regression adjustment from Callaway and Sant'Anna (2021) (gray diamonds). Dependent variables: the regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A13: Event study estimates of large shocks to GRP by skill-biased employment



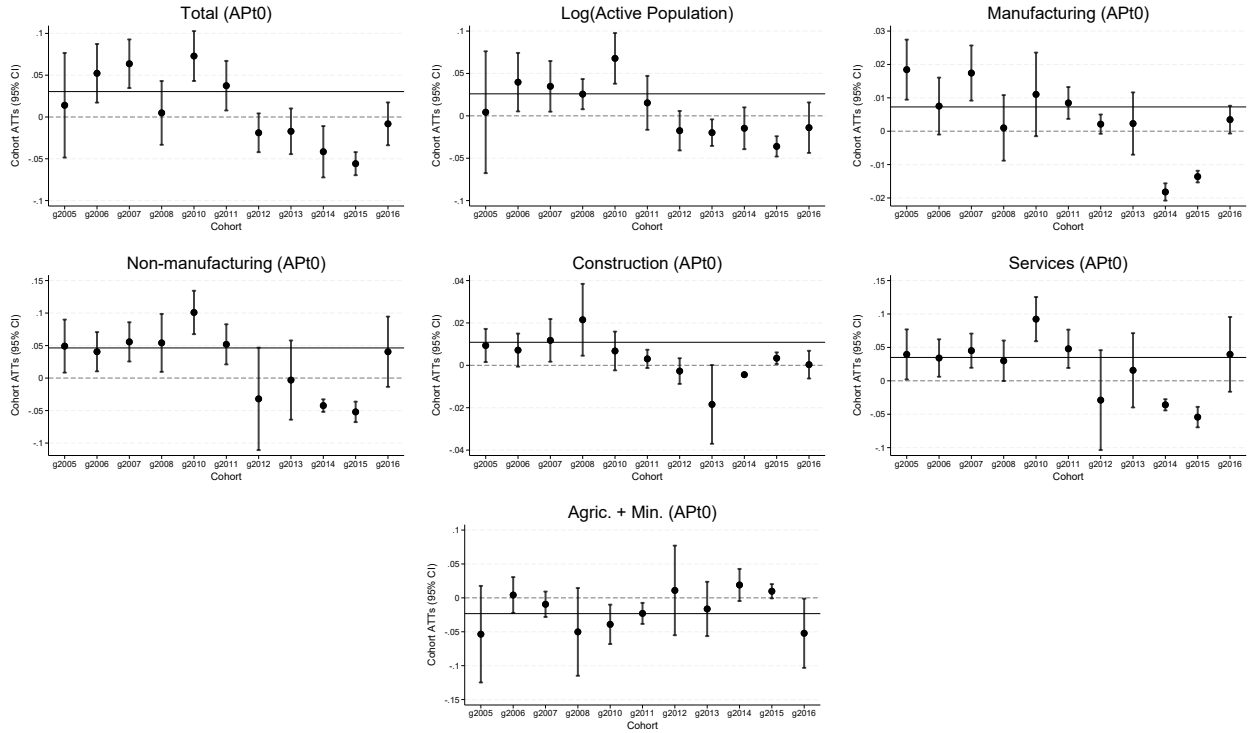
Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant'Anna (2021). Dependent variables: the k -year change in regional employment over active population by: high-skill (tertiary education); middle-skill (higher secondary education); low-skill (lower secondary education and less); STEM (workers employed in science and technology activities and with tertiary education). Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A14: Event study estimates of large shocks to GRP by skill-biased employment with active population fixed



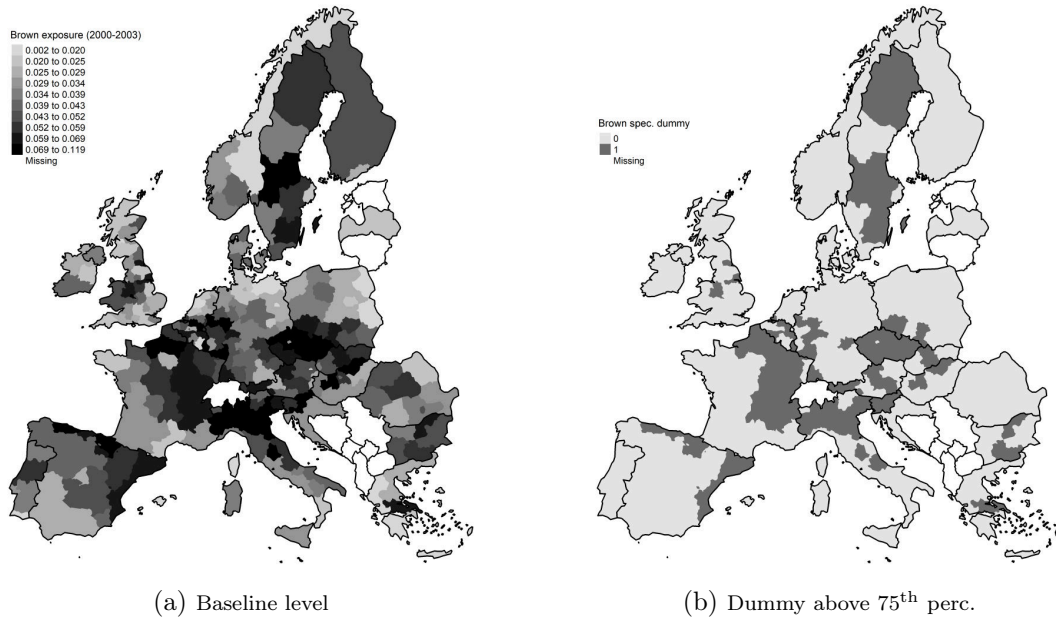
Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant'Anna (2021). Dependent variables: the k -year change in regional employment over active population by: high-skill (tertiary education); middle-skill (higher secondary education); low-skill (lower secondary education and less); STEM (workers employed in science and technology activities and with tertiary education). In all plots with APt₀, active population is fixed at baseline. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A15: Cohort-specific ATTs of large shocks to GRP with active population fixed



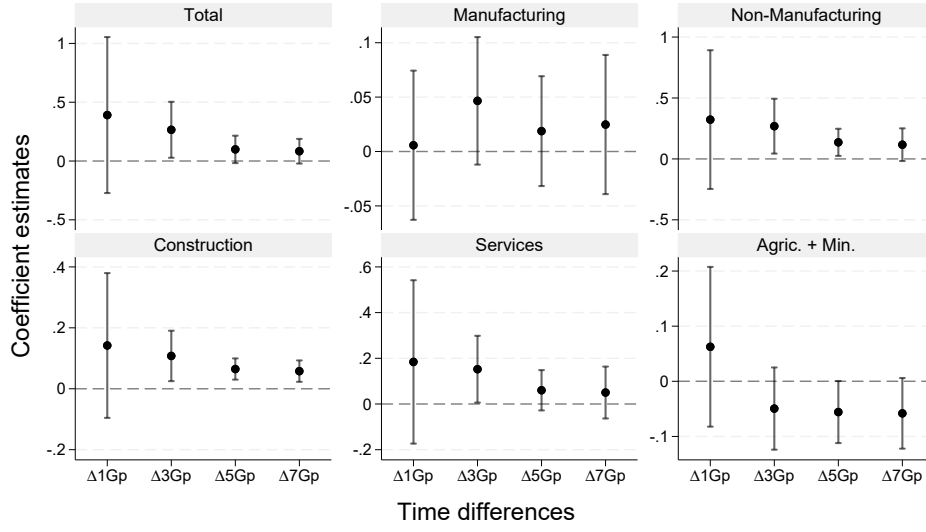
Notes. These figures show the ATT by cohort resulting from estimating Equation 5 with a regression adjustment estimator within the Callaway and Sant'Anna (2021) framework. Cohorts are identified by the year of exposure to treatment. Dependent variables: log of total employment; log of active population; total, manufacturing, non-manufacturing (utilities, construction, services), services and agriculture + mining. In all plots with APt0, active population is fixed at baseline. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. The solid black line represents the aggregate ATT. Region-clustered standard errors in parentheses. Number of regions: 278. 95% confidence intervals.

Figure A16: Baseline brown exposure by NUTS2 region and dummy that identifies specialization



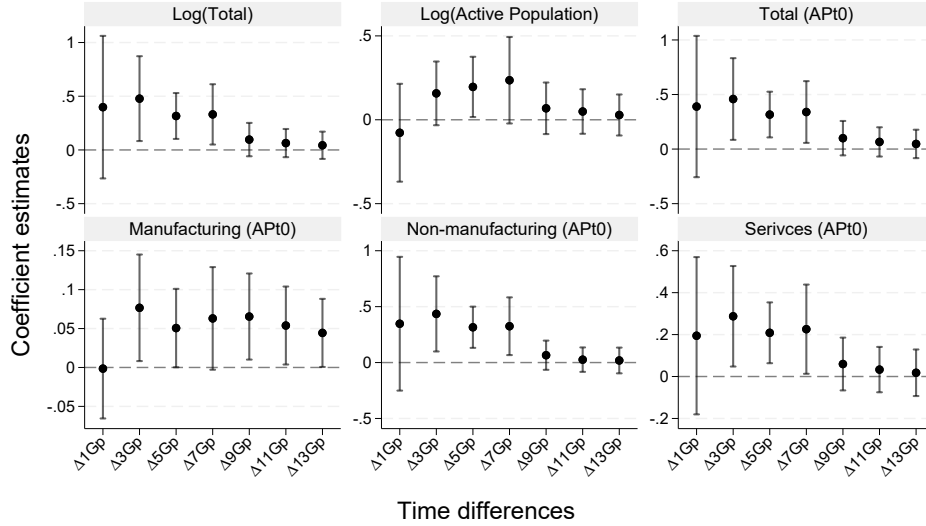
Notes. These maps show the baseline brown exposure (panel (a)) and a dummy that identifies values higher than the 75th percentile (panel (b)) by NUTS2 regions in the EU. Panel (a) levels correspond to deciles, and are weighted by the share of the regional population over the EU one.

Figure A17: 2SLS estimates of GRP on brown-exposed regional employment



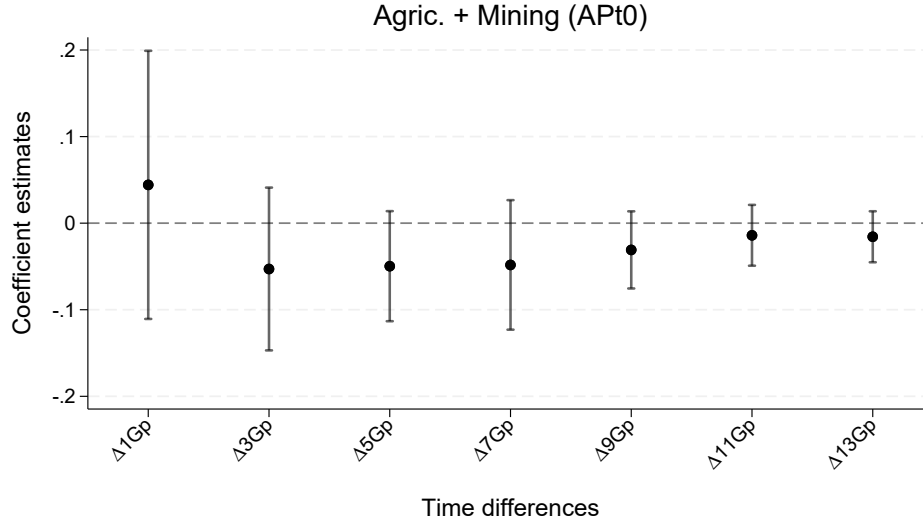
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five- and seven-year changes. Dependent variables: the k -year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. The sample is restricted to brown-exposed regions as defined in text. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 65. KP F-stats: 1.6; 7.3; 22.0; 25.9. CD F-stats: 2.8; 13.8; 31.6; 25.6. 95% confidence intervals.

Figure A18: 2SLS estimates of GRP on brown-exposed regional employment and active population over a longer time horizon and fixed active population



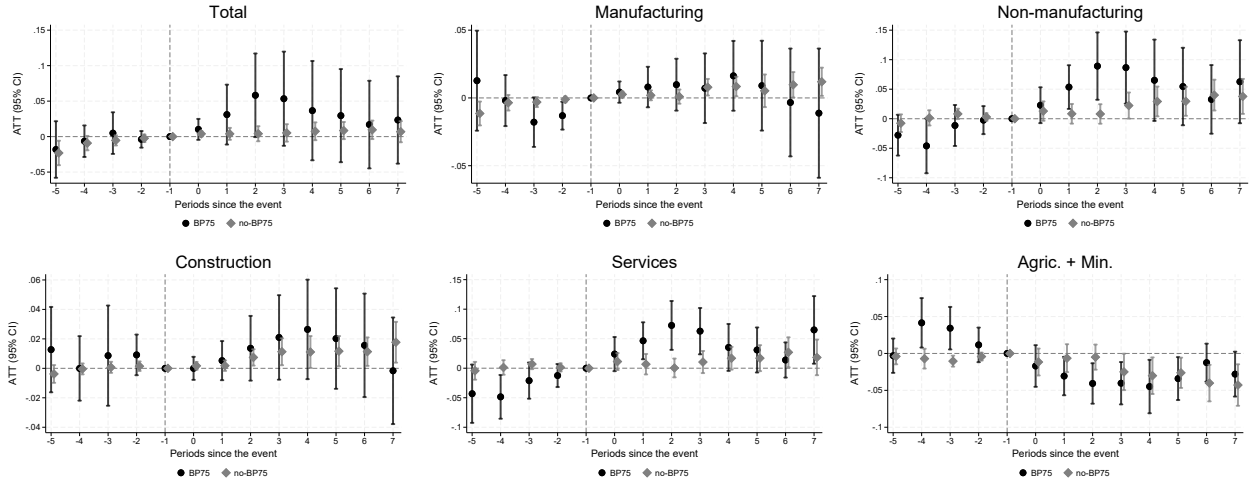
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variables: the k -year change in log of total employment; log of active population; total, manufacturing, non-manufacturing (utilities, construction, services), services, all with active population fixed at baseline. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. The sample is restricted to brown-exposed regions as defined in text. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 65. KP F-stats: 1.6; 7.3; 22.0; 25.9; 31.6; 30.4; 35.0. CD F-stats: 2.8; 13.8; 31.6; 25.6; 73.3; 87.8; 54.0. 95% confidence intervals.

Figure A19: 2SLS estimates of GRP on brown-exposed regional primary-employment and active population over a longer time horizon and fixed active population



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five-, seven-, nine-, eleven- and thirteen- year changes. Dependent variables: the k -year change in regional employment in agriculture and mining, with active population fixed at baseline. The endogenous variable, $\Delta GRP_{r,t_k}$, refers to the change in the GRP measure in region r between t and $t-t_k$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. The sample is restricted to brown-exposed regions as defined in text. Estimates are weighted by the share of regional population over the EU one, at baseline. Region-clustered standard errors in parentheses. Number of regions: 65. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2. 95% confidence intervals.

Figure A20: Event study estimates of large shocks to GRP splitting by brown exposure



Notes. These plots show the results of the event study specification of Equation 5. They employ a regression adjustment from Callaway and Sant'Anna (2021). Dependent variables: the regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. Treatment is defined as a positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. The sample is split by brown-specialized regions. Region-clustered standard errors in parentheses. Number of brown-exposed regions: 65. Number of non-brown-exposed regions: 213. 95% confidence intervals.

A.2 Tables

Table A1: Descriptive statistics of main variables

	N	Mean	SD	p1	p50	p99
<i>Outcomes</i>						
Total employment over active pop.	4170	0.9104	0.0524	0.7214	0.9224	0.9734
t-t ₃ Total employment over active pop.	3336	0.0011	0.0349	-0.1240	0.0032	0.0927
Manufacturing employment over active pop.	4170	0.1312	0.0583	0.0313	0.1227	0.2827
t-t ₃ Manufacturing employment over active pop.	3336	-0.0057	0.0155	-0.0432	-0.0054	0.0380
Non-manufacturing employment over active pop.	4170	0.6886	0.1199	0.2944	0.7027	0.8814
t-t ₃ Non-manufacturing employment over active pop.	3336	0.0109	0.0535	-0.0934	0.0126	0.0882
Construction employment over active pop.	4170	0.0675	0.0177	0.0327	0.0663	0.1209
t-t ₃ Construction employment over active pop.	3336	-0.0020	0.0132	-0.0493	-0.0005	0.0299
Services employment over active pop.	4170	0.6133	0.1214	0.2496	0.6266	0.8123
t-t ₃ Services employment over active pop.	3336	0.0121	0.0497	-0.0590	0.0114	0.0756
Agriculture + mining employment over active pop.	4170	0.0906	0.1042	-0.0879	0.0661	0.5283
t-t ₃ Agriculture + mining employment over active pop.	3336	-0.0042	0.0494	-0.0793	-0.0025	0.0513
<i>Green penetration and green patents SSIV</i>						
Regional green penetration	4170	0.548829	0.468924	0.015361	0.416036	2.180873
t-t ₃ regional green penetration	3336	0.082808	0.175823	-0.298016	0.046272	0.692110
Regional green patents SSIV	4170	0.000060	0.000077	0.000000	0.000036	0.000364
t-t ₃ regional green patents SSIV	3336	0.000012	0.000021	-0.000004	0.000004	0.000110
<i>Controls</i>						
Population density (t0)	4170	448.4507	961.3419	16.7000	173.4750	3975.6001
Median age (t0)	4170	38.7253	2.6659	32.8000	38.9750	44.9273
Share of female population (t0)	4170	0.5178	0.0084	0.4942	0.5175	0.5400
Share of foreign-born population (t0)	4170	0.0458	0.0436	0.0021	0.0345	0.1755
Share of population with lower secondary edu. (t0)	4170	0.3977	0.1606	0.1326	0.3690	0.8394
Share of population with upper secondary edu. (t0)	4170	0.3926	0.1373	0.1007	0.3792	0.6732
Share of population with tertiary edu. (t0)	4170	0.1535	0.0682	0.0527	0.1519	0.3561
Share employed in manufacturing (t0)	4170	0.1556	0.0618	0.0495	0.1475	0.3164
Regional non-green penetration (t0)	4170	8.2605	6.7683	0.2647	6.1283	29.2330
Polluting activities exposure (t0)	4170	0.0440	0.0205	0.0133	0.0392	0.0992

Notes. This table shows the descriptive statistics of the main variables used in the analysis. It shows the number of observations (N), mean (Mean), standard deviation (SD), and the first, the fiftieth and the ninetieth percentiles (p1, p50, p99). We weight the variables by the share of regional population over the EU one.

Table A2: Green and polluting production by 2-digit industries

NACE2D	Label	Share Gp	Tot. Gp	Mean Gp	SD Gp	Max Gp	GHG int.
<i>Potentially green industries</i>							
33	Repair and installation of machinery and equipment	0.1844	383554.854	711.605	1368.634	8106.562	0.740
26	Manufacture of computer, electronic and optical products	0.1804	294572.305	541.493	1432.731	11602.843	0.300
30	Manufacture of other transport equipment	0.1764	239995.366	441.168	916.273	7482.641	0.610
27	Manufacture of electrical equipment	0.1299	383540.545	705.038	1798.052	14265.906	0.300
28	Manufacture of machinery and equipment n.e.c.	0.0836	524287.359	963.764	2317.087	17440.078	0.540
16	Manufacture of wood and of products of wood and cork	0.0015	2308.279	4.911	10.564	68.902	0.880
29	Manufacture of motor vehicles	0.0003	2422.361	4.923	25.723	251.283	0.610
<i>Non-green industries</i>							
10	Manufacture of food products	0.0000	0.000	0.000	0.000	0.000	1.450
11	Manufacture of beverages	0.0000	0.000	0.000	0.000	0.000	1.450
12	Manufacture of tobacco products	0.0000	0.000	0.000	0.000	0.000	1.450
13	Manufacture of textiles	0.0000	0.000	0.000	0.000	0.000	0.970
14	Manufacture of wearing apparel	0.0000	0.000	0.000	0.000	0.000	0.970
15	Manufacture of leather and related products	0.0000	0.000	0.000	0.000	0.000	0.970
17	Manufacture of paper and paper products	0.0000	0.000	0.000	0.000	0.000	1.180
18	Printing and reproduction of recorded media	0.0000	0.000	0.000	0.000	0.000	1.180
22	Manufacture of rubber and plastic products	0.0000	0.000	0.000	0.000	0.000	0.940
31	Manufacture of furniture	0.0000	0.000	0.000	0.000	0.000	0.740
32	Other manufacturing	0.0000	0.000	0.000	0.000	0.000	0.740
<i>Polluting industries</i>							
24	Manufacture of basic metals	0.0216	63525.056	126.544	202.420	1024.372	4.230
25	Manufacture of fabricated metal products	0.0137	75930.470	139.578	262.518	1956.398	4.230
21	Manufacture of basic pharmaceutical products	0.0000	0.000	0.000	0.000	0.000	5.110
20	Manufacture of chemicals and chemical products	0.0163	60694.073	280.991	590.525	3945.616	5.110
23	Manufacture of other non-metallic mineral products	0.0314	95324.577	186.545	312.939	1473.388	7.780
19	Manufacture of coke and refined petroleum products	0.0000	0.000	0.000	0.000	0.000	44.990

Notes: Authors' elaboration on PRODCOM data. Production values are deflated to have data at constant prices, with 2020 as the base year. Column 1 reports the share that green production of each industry represents in total green production. Column 2 reports total sold green production from 2003 to 2017, with data in million of €. Column 3 and 4 report the mean and standard deviation of green production from 2003 to 2017, with data in million of €. Column 5 reports the maximum value of an industry-year of sold green production, with data in million of €. Columns 6 report the average GHG intensity for each industry computed with WIOD. Polluting industries are identified as the 5 industries with the highest average GHG intensity.

Table A3: Top NUTS2 regions by average GRP

Region	GRP	Region	GRP
DK - Midtjylland	2.650	DE - Sachsen-Anhalt	0.771
DK - Syddanmark	2.547	FR - Alsace	0.771
DE - Oberpfalz	2.141	DE - Schleswig-Holstein	0.759
DE - Mittelfranken	2.127	SE - Västsverige	0.752
DK - Nordjylland	2.032	CZ - Střední Morava	0.731
DE - Tübingen	1.805	AT - Vorarlberg	0.730
DE - Schwaben	1.728	DE - Münster	0.726
DE - Stuttgart	1.658	SE - Sydsverige	0.720
DE - Freiburg	1.573	ES - Aragón	0.720
DE - Bremen	1.510	DE - Köln	0.712
DE - Karlsruhe	1.498	AT - Wien	0.704
AT - Oberösterreich	1.491	FI - Etelä-Suomi	0.702
DE - Unterfranken	1.473	FR - Rhône-Alpes	0.700
DE - Hamburg	1.436	CZ - Moravskoslezsko	0.700
DE - Detmold	1.407	HR - Jadranska Hrvatska	0.699
DE - Arnsberg	1.364	AT - Kärnten	0.689
DE - Dresden	1.300	FR - Midi-Pyrénées	0.681
DE - Oberfranken	1.278	AT - Niederösterreich	0.676
DE - Oberbayern	1.237	DE - Leipzig	0.662
ES - País Vasco	1.231	DE - Berlin	0.661
DE - Gießen	1.228	FI - Itä-Suomi	0.640
SE - Småland med öarna	1.216	IT - Toscana	0.636
IT - Friuli-Venezia Giulia	1.214	DE - Brandenburg	0.623
IT - Emilia-Romagna	1.185	ES - La Rioja	0.614
SE - Östra Mellansverige	1.148	AT - Tirol	0.606
IT - Lombardia	1.054	UK - North Eastern Scotland	0.603
DE - Thüringen	1.047	IT - Umbria	0.601
IT - Veneto	1.021	IT - Abruzzo	0.599
DE - Kassel	0.999	DE - Mecklenburg-Vorpommern	0.573
DE - Niederbayern	0.992	DE - Trier	0.571
AT - Steiermark	0.986	CZ - Severovýchod	0.566
DE - Chemnitz	0.977	FR - Pays de la Loire	0.562
FI - Länsi-Suomi	0.966	CZ - Jihovýchod	0.557
ES - Comunidad Foral de Navarra	0.953	FR - Limousin	0.557
DK - Sjælland	0.940	UK - Shropshire and Staffordshire	0.551
IT - Piemonte	0.931	ES - Principado de Asturias	0.549
SE - Norra Mellansverige	0.931	UK - East Wales	0.548
DE - Saarland	0.931	FR - Bourgogne	0.547
IT - Marche	0.922	SE - Övre Norrland	0.545
DE - Düsseldorf	0.920	DE - Lüneburg	0.539
DE - Weser-Ems	0.915	FR - Centre (FR)	0.539
DE - Braunschweig	0.911	UK - Hampshire and Isle of Wight	0.535
DE - Hannover	0.877	CZ - Jihozápad	0.531
DE - Darmstadt	0.849	UK - Dorset and Somerset	0.529
IT - Liguria	0.847	HU - Közép-Dunántúl	0.528
FR - Ile de France	0.825	FR - Franche-Comté	0.521
DE - Rheinhessen-Pfalz	0.819	FR - Haute-Normandie	0.514
DK - Hovedstaden	0.805	IT - Campania	0.509
DE - Koblenz	0.788	ES - Cantabria	0.505
SE - Mellersta Norrland	0.783	CZ - Severozápad	0.504
FI - Etelä-Suomi	0.778	BE - Prov. Hainaut	0.503

Notes. This table shows the NUTS2 regions for which their average green manufacturing penetration from 2003 to 2017 is higher than the average across NUTS regions.

Table A4: Top NUTS2 regions by the average three-year change in GRP

Region	Δ_3 GRP	Region	Δ_3 GRP
DK - Midtjylland	0.831	DE - Saarland	0.152
DK - Syddanmark	0.680	FR - Midi-Pyrénées	0.141
DK - Nordjylland	0.536	DE - Schleswig-Holstein	0.140
AT - Oberösterreich	0.506	PL - Podkarpackie	0.139
AT - Steiermark	0.364	PL - Dolnośląskie	0.136
DE - Tübingen	0.361	CZ - Severozápad	0.135
DE - Oberpfalz	0.352	CZ - Střední Čechy	0.134
DE - Stuttgart	0.336	DE - Koblenz	0.134
DE - Schwaben	0.334	SK - Západné Slovensko	0.128
DE - Mittelfranken	0.331	SI - Vzhodna Slovenija	0.127
AT - Vorarlberg	0.313	DE - Düsseldorf	0.125
DK - Sjælland	0.298	DE - Darmstadt	0.123
AT - Wien	0.296	ES - Comunidad Foral de Navarra	0.121
DE - Bremen	0.296	PL - Opolskie	0.119
DE - Freiburg	0.290	DE - Berlin	0.116
DE - Dresden	0.286	PL - Śląskie	0.114
DE - Gießen	0.283	SK - Stredné Slovensko	0.114
DE - Unterfranken	0.279	FI - Länsi-Suomi	0.113
DE - Hamburg	0.278	DE - Leipzig	0.112
DE - Karlsruhe	0.276	PL - Zachodniopomorskie	0.111
AT - Kärnten	0.259	CZ - Praha	0.111
AT - Niederösterreich	0.249	DE - Münster	0.109
DE - Detmold	0.248	ES - Aragón	0.109
DE - Oberbayern	0.247	SE - Småland med öarna	0.107
CZ - Střední Morava	0.238	DE - Mecklenburg-Vorpommern	0.107
DE - Arnsberg	0.237	PL - Wielkopolskie	0.105
DK - Hovedstaden	0.233	SI - Zahodna Slovenija	0.102
AT - Tirol	0.231	FR - Pays de la Loire	0.098
DE - Oberfranken	0.231	DE - Sachsen-Anhalt	0.098
CZ - Severovýchod	0.209	DE - Trier	0.098
PL - Pomorskie	0.201	FR - Ile de France	0.096
CZ - Jihozápad	0.194	ES - La Rioja	0.093
DE - Kassel	0.194	SK - Bratislavský kraj	0.091
DE - Niederbayern	0.190	DE - Köln	0.090
AT - Salzburg	0.178	FI - Etelä-Suomi	0.090
DE - Braunschweig	0.176	PL - Lubuskie	0.089
CZ - Jihovýchod	0.170	ES - Principado de Asturias	0.088
AT - Burgenland	0.170	DE - Brandenburg	0.087
DE - Thüringen	0.169	DE - Lüneburg	0.086
CZ - Moravskoslezsko	0.167	FR - Poitou-Charentes	0.084
DE - Hannover	0.164	PL - Kujawsko-pomorskie	0.084
DE - Weser-Ems	0.161	FR - Alsace	0.082
ES - País Vasco	0.159	FI - Itä-Suomi	0.082
FR - Alsace	0.082		

Notes. This table shows the NUTS2 regions for which their three-year average GRP from 2003 to 2017 is higher than the average across NUTS regions.

Table A5: GRP on regional employment by skill level and STEM employment

	(1)	(2)	(3)	(4)
<i>Panel A:</i>	<i>Low skill</i>	<i>Medium skill</i>	<i>High skill</i>	<i>STEM</i>
$\Delta GRP_{r,t3}$	0.057*** (0.019)	0.036 (0.029)	0.048** (0.021)	0.045** (0.019)
<i>N</i>	3336	3336	3336	3336
Estimator	2SLS	2SLS	2SLS	2SLS
FS coeff.	1658.106***	1658.106***	1658.106***	1658.106***
KP F-Stat	53.4	53.4	53.4	53.4
CD F-Stat	79.4	79.4	79.4	79.4
Controls	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population by low, medium and high skill and employment in STEM. Employment with low-skill is given by employed people with less than primary, primary and lower secondary education. Employment with medium-skill is given by employed people with upper secondary and post-secondary non-tertiary education. Lastly, employment with high-skill is given by employed people with tertiary education. STEM employment is given by people with tertiary education and employed in science and technology. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. All columns show estimates related to the green patents instrument. All columns report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration measure, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Top 5 Rotemberg weights of green patents SSIV

NACE2	Label	Rotemberg weight	Emp. Share (t_0)
28	Manufacture of machinery and equipment n.e.c.	0.301	0.111
27	Manufacture of electrical equipment	0.250	0.109
29	Manufacture of motor vehicles	0.091	0.090
20	Manufacture of chemicals and chemical products	0.066	0.120
26	Manufacture of computer, electronic and optical products	0.063	0.129
PRODCOM	Label		
28211354	Electric furnaces and ovens (excluding induction- and resistance-heated)		
28251431	Machinery and apparatus for filtering and purifying gases		
28112150	Steam turbines for electricity generation		
27201100	Primary cells and primary batteries		
27902060	Light-emitting diodes (LEDs)		
27112680	Photovoltaic AC generators		
29102450	Motor vehicles, with only electric motor for propulsion		
29102430	Motor vehicles, with hybrid propulsion		
29104313	Road tractors for semi-trailers with only electric motor for propulsion		
20595997	Biofuels (diesel substitute)		
26517015	Electronic thermostats		
26515313	Electronic gas or smoke analysers		
26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus		

Notes. This table reports 2-digit manufacturing sectors with the highest five Rotemberg weights associated to the green patents-SSIV (Goldsmith-Pinkham et al., 2020). Further, it reports the baseline (avg. 2000-2003) employment share within manufacturing of these sectors. Lastly, it reports example of green goods that fall within these sectors.

Table A7: GRP on regional employment, excluding NACE sector 28

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.044*** (0.010)	0.418*** (0.111)	0.008* (0.005)	0.131*** (0.039)	0.037*** (0.012)	0.301*** (0.088)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.016*** (0.004)	0.147*** (0.038)	0.022** (0.011)	0.136** (0.063)	-0.002 (0.012)	-0.014 (0.060)
<i>N</i>	3336	3336	3336	3336	3336	3336
<i>Estimator</i>	OLS	2SLS	OLS	2SLS	OLS	2SLS
<i>FS coeff.</i>		944.643***		944.643***		944.643***
<i>KP F-Stat</i>		19.2		19.2		19.2
<i>CD F-Stat</i>		38.3		38.3		38.3
<i>Controls</i>	✓	✓	✓	✓	✓	✓
<i>Country FE</i>	✓	✓	✓	✓	✓	✓
<i>Year FE</i>	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A5, we exclude NACE2 sector 28. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: GRP on regional employment, excluding NACE sector 27

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.028*** (0.007)	0.239** (0.098)	0.012*** (0.003)	0.063* (0.035)	0.019*** (0.007)	0.191** (0.084)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.006*** (0.002)	0.133*** (0.044)	0.014** (0.005)	0.030 (0.060)	-0.002 (0.006)	-0.016 (0.058)
<i>N</i>	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1193.462***		1193.462***		1193.462***
KP F-Stat		11.9		11.9		11.9
CD F-Stat		26.0		26.0		26.0
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A5, we exclude NACE2 sector 27. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: GRP on regional employment, excluding NACE sector 29

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.028*** (0.007)	0.152*** (0.037)	0.010*** (0.003)	0.056*** (0.015)	0.022*** (0.008)	0.113*** (0.037)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.007*** (0.002)	0.073*** (0.013)	0.016** (0.007)	0.029 (0.033)	-0.004 (0.007)	-0.017 (0.032)
<i>N</i>	3336	3336	3336	3336	3336	3336
<i>Estimator</i>	OLS	2SLS	OLS	2SLS	OLS	2SLS
<i>FS coeff.</i>		2009.240***		2009.240***		2009.240***
<i>KP F-Stat</i>		55.3		55.3		55.3
<i>CD F-Stat</i>		91.1		91.1		91.1
<i>Controls</i>	✓	✓	✓	✓	✓	✓
<i>Country FE</i>	✓	✓	✓	✓	✓	✓
<i>Year FE</i>	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A5, we exclude NACE2 sector 29. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: GRP on regional employment, excluding NACE sector 20

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.031*** (0.007)	0.118*** (0.023)	0.010*** (0.003)	0.042*** (0.011)	0.023*** (0.008)	0.089*** (0.025)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.008*** (0.002)	0.057*** (0.008)	0.016** (0.007)	0.023 (0.022)	-0.003 (0.008)	-0.013 (0.022)
<i>N</i>	3336	3336	3336	3336	3336	3336
<i>Estimator</i>	OLS	2SLS	OLS	2SLS	OLS	2SLS
<i>FS coeff.</i>		2225.323***		2225.323***		2225.323***
<i>KP F-Stat</i>		121.6		121.6		121.6
<i>CD F-Stat</i>		132.5		132.5		132.5
<i>Controls</i>	✓	✓	✓	✓	✓	✓
<i>Country FE</i>	✓	✓	✓	✓	✓	✓
<i>Year FE</i>	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A5, we exclude NACE2 sector 20. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: GRP on regional employment, excluding NACE sector 26

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.032*** (0.008)	0.166*** (0.044)	0.010*** (0.003)	0.040*** (0.015)	0.027*** (0.009)	0.134*** (0.039)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.009*** (0.003)	0.085*** (0.019)	0.019*** (0.007)	0.043 (0.032)	-0.005 (0.007)	-0.008 (0.031)
<i>N</i>	3336	3336	3336	3336	3336	3336
<i>Estimator</i>	OLS	2SLS	OLS	2SLS	OLS	2SLS
<i>FS coeff.</i>		1735.026***		1735.026***		1735.026***
<i>KP F-Stat</i>		31.5		31.5		31.5
<i>CD F-Stat</i>		65.2		65.2		65.2
<i>Controls</i>	✓	✓	✓	✓	✓	✓
<i>Country FE</i>	✓	✓	✓	✓	✓	✓
<i>Year FE</i>	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A5, we exclude NACE2 sector 26. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Correlation between green patents shift-share instrumental variable, industry employment shares and controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Green patents	NACE 27	NACE 26	NACE 28	NACE 29	NACE 20
$Share\ emp\ manu_{r,t0}$	0.0001* (0.0000)	0.7412*** (0.2843)	0.1400 (0.5863)	0.8849*** (0.2208)	0.1467 (0.3236)	0.6075 (0.4454)
$NGRP_{r,t0}$	0.0000*** (0.0000)	-0.0019 (0.0024)	0.0017 (0.0071)	-0.0024 (0.0023)	0.0087* (0.0046)	-0.0030 (0.0038)
<i>Observations</i>	254	254	254	254	254	254
<i>Country FE</i>	✓	✓	✓	✓	✓	✓

Notes: This table show the balance of the two main covariates for the pre-sample aggregate green patents-SSIV and each of the 2-digit manufacturing employment shares resulting to be within the top 5 Rotemberg weights. We include country fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 254. Due to data availability in baseline employment shares, we exclude the following regions: BG31, BG32, BG33, BG34, BG41, BG42, CY00, HR03, HR04, IS00, LV00, MT00, RO11, RO12, RO21, RO22, RO31, RO32, RO41, RO42, SK01, SK02, SK03, SK04. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Lee et al. (2022) valid t-ratio inference

<i>Panel A:</i>	<i>Total</i>	<i>Manufacturing</i>	<i>Non-manufacturing</i>
Coefficient	0.166	0.053	0.126
Unadj SE	0.028	0.012	0.046
1% CV of t	3.138	3.138	3.138
Adj SE	0.034	0.015	0.056
Adj UB	0.255	0.091	0.269
Adj LB	0.078	0.015	-0.017
FS F-stat	80.909	80.909	80.909
<i>Panel B:</i>	<i>Construction</i>	<i>Services</i>	<i>Agric. + Min.</i>
Coefficient	0.076	0.039	-0.013
Unadj SE	0.012	0.042	0.042
1% CV of t	3.138	3.138	3.138
Adj SE	0.015	0.051	0.052
Adj UB	0.115	0.171	0.12
Adj LB	0.038	-0.093	-0.146
FS F-stat	80.909	80.909	80.909

Notes: This table applies the methodology from Lee et al. (2022) to estimate valid t-ratio inference for instrumental variables. The estimates the command works on are even columns of Table 1.

Table A14: GRP on regional employment with extended controls

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.029*** (0.007)	0.205*** (0.040)	0.010*** (0.003)	0.051*** (0.014)	0.023*** (0.008)	0.149*** (0.041)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.007*** (0.002)	0.081*** (0.015)	0.016** (0.007)	0.059 (0.036)	-0.003 (0.007)	0.005 (0.036)
<i>N</i>	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1611.003***		1611.003***		1611.003***
KP F-Stat		49.7		49.7		49.7
CD F-Stat		71.7		71.7		71.7
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include population density, median age, share of female population, share of foreign population, share of employed people with secondary education, share of employed people with tertiary education, share of employment in manufacturing and the regional non-green penetration. The share of employment in manufacturing and the regional non-green penetration are interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 270. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: GRP on regional employment with either NUTS1 or NUTS2 fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.353*** (0.091)	0.459*** (0.148)	0.059*** (0.022)	0.069** (0.031)	0.259*** (0.073)	0.339*** (0.114)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.131*** (0.033)	0.172*** (0.055)	0.114** (0.053)	0.150** (0.073)	0.035 (0.055)	0.051 (0.072)
<i>N</i>	3336	3336	3336	3336	3336	3336
<i>Estimator</i>	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
<i>KP F-Stat</i>	17.9	10.6	17.9	10.6	17.9	10.6
<i>CD F-Stat</i>	34.3	24.2	34.3	24.2	34.3	24.2
<i>Controls</i>	✓	✓	✓	✓	✓	✓
<i>NUTS1 FE</i>	✓		✓		✓	
<i>NUTS2 FE</i>		✓		✓		✓
<i>Year FE</i>	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show 2SLS estimates related to the green patents instrument including NUTS 1 and year fixed effects, while columns (2), (4) and (6) show the ones related to the green patents instrument including NUTS 2 and year fixed effects. All columns report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: GRP on regional employment with automation controls

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.046*** (0.008)	0.234*** (0.057)	0.020*** (0.003)	0.093*** (0.022)	0.042*** (0.010)	0.165*** (0.046)
$\Delta Robot\ penetration_{r,t3}$	-0.009* (0.005)	-0.035*** (0.012)	-0.007** (0.003)	-0.017*** (0.005)	0.004 (0.005)	-0.013 (0.010)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.010*** (0.003)	0.086*** (0.021)	0.034*** (0.008)	0.062* (0.032)	-0.017** (0.008)	-0.024 (0.030)
$\Delta Robot\ penetration_{r,t3}$	0.003** (0.001)	-0.007* (0.004)	-0.000 (0.004)	-0.004 (0.007)	-0.006** (0.003)	-0.005 (0.005)
<i>N</i>	2406	2406	2406	2406	2406	2406
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1306.576***		1306.576***		1306.576***
KP F-Stat		26.8		26.8		26.8
CD F-Stat		52.1		52.1		52.1
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. The additional control is the 3 years change in regional automation exposure. Besides this last one, all the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 207. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: GRP on regional employment with balanced sample by automation data

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.043*** (0.008)	0.162*** (0.037)	0.018*** (0.003)	0.057*** (0.015)	0.043*** (0.010)	0.140*** (0.033)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.011*** (0.003)	0.071*** (0.013)	0.034*** (0.008)	0.056** (0.025)	-0.019** (0.008)	-0.035 (0.021)
<i>N</i>	2484	2484	2484	2484	2484	2484
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1708.035***		1708.035***		1708.035***
KP F-Stat		56.1		56.1		56.1
CD F-Stat		99.3		99.3		99.3
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. The sample is restricted depending on availability of automation data at the regional level. Region clustered standard errors in parentheses. Number of regions: 207. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: GRP on regional employment with NUTS 1 clustered standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.028*** (0.010)	0.166*** (0.053)	0.010*** (0.004)	0.053*** (0.019)	0.022** (0.011)	0.126** (0.052)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.007** (0.003)	0.076*** (0.019)	0.016* (0.009)	0.039 (0.040)	-0.004 (0.009)	-0.013 (0.037)
<i>N</i>	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1658.106***		1658.106***		1658.106***
KP F-Stat		38.3		38.3		38.3
CD F-Stat		79.4		79.4		79.4
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. NUTS 1 clustered standard errors in parentheses. Number of regions: 278. Number of NUTS1: 100. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: GRP on regional employment, removing outliers in outcome and green penetration

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.046*** (0.010)	0.132*** (0.042)	0.015*** (0.002)	0.050** (0.021)	0.035*** (0.009)	0.189*** (0.042)
<i>N</i>	2592	2592	2556	2556	2568	2568
FS coeff.		1611.067***		1463.506***		1653.461***
KP F-Stat		30.3		21.6		32.2
CD F-Stat		86.0		69.9		89.3
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.008** (0.004)	0.096*** (0.020)	0.028*** (0.007)	0.083*** (0.029)	0.000 (0.004)	-0.069*** (0.023)
<i>N</i>	2616	2616	2580	2580	2664	2664
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1530.096***		1678.681***		1660.371***
KP F-Stat		27.1		33.2		32.1
CD F-Stat		76.8		92.9		93.3
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Each pair of columns exclude regions where either the dependent variable or the endogenous variable have at least once a value above (below) the top (bottom) 1% of that variable. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: GRP on regional employment, excluding small regions

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A:</i>	<i>Total</i>		<i>Manufacturing</i>		<i>Non-manufacturing</i>	
$\Delta GRP_{r,t3}$	0.028*** (0.007)	0.168*** (0.039)	0.010*** (0.003)	0.054*** (0.015)	0.022*** (0.008)	0.126*** (0.036)
<i>Panel B:</i>	<i>Construction</i>		<i>Services</i>		<i>Agric. + Min.</i>	
$\Delta GRP_{r,t3}$	0.007*** (0.002)	0.077*** (0.014)	0.016** (0.007)	0.039 (0.030)	-0.004 (0.007)	-0.012 (0.031)
<i>N</i>	3288	3288	3288	3288	3288	3288
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1658.106***		1658.106***		1658.106***
KP F-Stat		53.4		53.4		53.4
CD F-Stat		79.4		79.4		79.4
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and $t-3$. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. All columns exclude regions where population density at baseline exhibits a value above (below) the top (bottom) 1%. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Positive and negative weights from the TWFE regression

	N ATTs	Sum of weights
Positive Weights	1141	1.0614
Negative Weights	135	-.0614
Total	1276	1

Notes. This table shows the weights attached to the two-way fixed effects regressions computed as in De Chaisemartin and d'Haultfoeuille (2020).

Table A22: Balance table by baseline specialization in brown exposure

Variable	Not-BP75	BP75	Diff. (BP75-NBP75)
Total employment over active pop.	0.909 (0.0543)	0.914 (0.0462)	0.0041 (0.0077)
Non-manufacturing employment over active pop.	0.694 (0.1330)	0.673 (0.0632)	-0.0214 (0.0131)
Population density (t0)	493.477 (1078.0203)	312.031 (422.9457)	-181.4457* (99.5077)
Median age (t0)	38.516 (2.7258)	39.358 (2.3669)	0.8414* (0.4711)
Share of female population (t0)	0.518 (0.0090)	0.517 (0.0061)	-0.0009 (0.0010)
Share of foreign-born population (t0)	0.044 (0.0451)	0.052 (0.0389)	0.0076 (0.0069)
Share of population with lower secondary edu. (t0)	0.385 (0.1628)	0.437 (0.1470)	0.0519* (0.0292)
Share of population with upper secondary edu. (t0)	0.392 (0.1325)	0.394 (0.1509)	0.0014 (0.0266)
Share of population with tertiary edu. (t0)	0.161 (0.0715)	0.131 (0.0513)	-0.0299*** (0.0110)
Share employed in manufacturing (t0)	0.136 (0.0498)	0.217 (0.0543)	0.0810*** (0.0109)
Regional non-green penetration (t0)	6.644 (5.4745)	13.159 (7.8702)	6.5148*** (1.3654)
t-t ₃ regional green penetration	0.080 (0.1671)	0.093 (0.1997)	0.0130 (0.0132)
t-t ₃ regional green patents SSIV	0.000 (0.0000)	0.000 (0.0000)	0.0000 (0.0000)
Pr. large GRP shock	0.422 (0.4939)	0.738 (0.4401)	0.3158*** (0.0831)
Observations	3195	975	4170

Notes. If t0 is present then values are taken at baseline, i.e. an average between 2000 and 2003. * p<0.10, ** p<0.05, *** p<0.01.

B Online Appendix

B.1 Main employment data

Total employment. Source: Eurostat - LFS. links:

- NACE Rev. 2 (2008-2017) https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2en2/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfemp;

- NACE Rev. 1.1 (2000-2007) https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2en1/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfemp.

The data concerns total employment levels by NUTS2 and year, from 2000 to 2017. The division in NACE Rev. 2 and NACE Rev. 1.1 does not imply any harmonization for employment data. We focus on employment for people older than 15 years old, of both sexes. NUTS2 regional codes have been harmonized to the NUTS 2016 changes. This implies harmonizing changes in regions definitions.³⁴ Employment data are reallocated for regions affected by splits or merges using proportionate coefficients. Remaining missing data has been interpolated and extrapolated using an inverse distance weighted interpolation.

Manufacturing employment. Source: Eurostat - SBS. links:

- NACE Rev. 2 (2008-2017) https://ec.europa.eu/eurostat/databrowser/view/sbs_r_nuts06_r2/default/table?lang=en&category=reg.reg_sbs;

- NACE Rev. 1.1 (2000-2007) https://ec.europa.eu/eurostat/databrowser/view/sbs_r_nuts03/default/table?lang=en&category=reg.reg_sbs.

The data concerns manufacturing employment, both aggregate and by 2-digit manufacturing industries, levels by NUTS2 and year, from 1995 to 2017. We map 2-digit employment NACE Rev. 1.1 data to 2-digit NACE Rev. 2 categories using country-specific weights, proportionally redistributing employment values when multiple mappings exist. These weights are calculated from country-product (PRODCOM) levels that leverage details about the crosswalk provided by Eurostat. For example NACE Rev. 1.1 sector 29 - Manufacture of machinery and equipment n.e.c. - is allocated as follows: for the 82% to NACE Rev. 2 sector 28 - Manufacture of machinery and equipment n.e.c.; for the 5% to NACE Rev. 2 sector 33 (Repair and installation of machinery and equipment); for the 9% to NACE Rev. 2 sector 27 (Manufacture of electrical equipment); the remaining 4% is allocated to NACE Rev. 2 sectors 25 (Manufacture of fabricated metal products, except machinery and equipment), 26 (Manufacture of computer, electronic and optical products) and 32 (Other manufacturing). Across countries, this allocation is mostly stable. For example, the allocation to NACE Rev. 2 sector 28 is at minimum 82.65% and at maximum 83.10%. The rest of the data management is identical to that described for total employment.

Utilities employment. Source: Eurostat - SBS. links:

- NACE Rev. 2 (2008-2017) https://ec.europa.eu/eurostat/databrowser/view/sbs_r_nuts06_r2/default/

³⁴For example, in the UK UKM3 was split into UKM8 and UKM9.

table?lang=en&category=reg.reg_sbs;

- NACE Rev. 1.1 (2000-2007) https://ec.europa.eu/eurostat/databrowser/view/sbs_r_nuts03/default/table?lang=en&category=reg.reg_sbs.

The data concerns utilities employment levels by NUTS2 and year, from 1995 to 2017. The crosswalk between NACE Rev. 1.1 and NACE Rev. 2 is a simple one-to-one of the NACE Rev. 1.1 category E to NACE Rev. 2 categories D and E, summed together. The rest of the data management is identical to that described for total employment.

Construction employment. Source: Eurostat - LFS. links:

- NACE Rev. 2 (2008-2017) https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2en2/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfemp;

- NACE Rev. 1.1 (2000-2007) https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2en1/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfemp.

The data concerns construction employment levels by NUTS2 and year, from 2000 to 2017. The crosswalk between NACE Rev. 1.1 and NACE Rev. 2 is a simple one-to-one of the NACE Rev. 1.1 category F to NACE Rev. 2 category F. The rest of the data management is identical to that described for total employment.

Services employment. Source: Eurostat - HTEC. links:

- NACE Rev. 2 (2008-2017) https://ec.europa.eu/eurostat/databrowser/view/htec_emp_reg2/default/table?lang=en&category=reg.reg_sct.reg_htec;

- NACE Rev. 1.1 (2000-2007) https://ec.europa.eu/eurostat/databrowser/view/htec_emp_reg/default/table?lang=en&category=reg.reg_sct.reg_htec.

The data concerns services employment levels by NUTS2 and year, from 2000 to 2017. The crosswalk between NACE Rev. 1.1 and NACE Rev. 2 is a simple one-to-one of the NACE Rev. 1.1 categories that identify KIS, summed together, to NACE Rev. 2 categories that identify KIS, summed together. KIS identification is defined by Eurostat. The rest of the data management is identical to that described for total employment.

Agriculture plus mining employment. Retrieved indirectly by subtracting from total employment employment in manufacturing, utilities, construction and services.

Employment by educational attainment. Source: Eurostat - LFS. link:

- https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2eedu/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfemp.

The data concerns employment levels by educational attainment levels by NUTS2 and year, from 2000 to 2017. The levels are the following: less than primary, primary and lower secondary education (ISCED 2011 levels 0-2); upper secondary and post-secondary non-tertiary education (ISCED 2011 levels 3 and 4); tertiary education (ISCED 2011 levels 5-8). The rest of the data management is identical to that described for total employment.

STEM. Source: Eurostat - HRST. link:

- https://ec.europa.eu/eurostat/databrowser/view/hrst_st_rcat/default/table?lang=en&category=reg.reg_sct.reg_hrst.

The data concerns employment levels of people with tertiary education (ISCED 2011) and employed in science and technology by NUTS2 and year, from 2000 to 2017. The rest of the data management is identical to that described for total employment.

B.2 Green production

Green goods list. Bontadini and Vona (2023) and Frattini et al. (2024) PRODCOM list of green potential goods is the union of the CLEG list and the German list, net of manually inspected goods with double usage.³⁵ As we discussed in the main text, we refine this list by: including newly items whose environmental benefits are now established; including all batteries, that were excluded due to their potential for double usage; including nuclear energy and biofuels, that enter as part of a broader low-carbon energy portfolio; excluding ambiguities in the classification arising from dual-use cases; including not only final green products but also their constituent components, with particular attention to those used in energy-efficient housing solutions. Table B1 shows the full list of green goods. The reason why the number of green goods in the current list (188) is lower than the original one (221) has to do with the fact that Eurostat harmonized PRODCOM codes up to 2007. From 2008 we do not harmonize product codes as none of them change classification up to the 2-digit manufacturing industry level. Hence, we effectively include more products.

Production. Source: Eurostat - PRODCOM. link:

- <https://ec.europa.eu/eurostat/databrowser/view/ds-056120/legacyMultiFreq/table?lang=en&category=prom>.

8-digit country-product level data is aggregated to country-2-digit industries data from 1995 to 2017. The data is then deflated using 2019 EUKLEMS value added deflators (link all but UK: all; link UK: UK). Non-green production is retrieved by subtracting green production from total production.

B.3 Patent data

Source: PATSTAT. link:

- <https://www.epo.org/en/searching-for-patents/business/patstat>.

Patent data is retrieved from PATSTAT Online database, which is provided by the European Patent Office (EPO). We obtained access by subscription that cost around EUR 700 per year. For each patent application, the patent office assigns NACE codes associated with it following Van Looy et al. (2014). The concordance by Van Looy et al. (2014) builds on Schmoch et al. (2003), and assigns CPC classes to sectors according to the

³⁵The CLEG list is itself the union of the following lists: the Plurilateral Environmental Goods and Services (PEGS) list developed by the OECD itself, the list suggested by the Asian Pacific Economic Cooperation (APEC) forum and the list stipulated by the WTO Friends group.

dominant industrial affiliation (NACE Rev. 2) of patent holders. We classify a patent as green if at least one CPC code associated with it starts with Y.

B.4 Economic-Socio-demographic data

Active population. Source: Eurostat - LFS. link:

- https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfsd2pwn/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfpop.

The data concerns active population levels of the local population older than 15 years by NUTS2 and year, from 2000 to 2017. The data management is identical to that described for total employment.

Population density. Source: Eurostat - DEMS. link:

- https://ec.europa.eu/eurostat/databrowser/view/demo_r_d3dens/default/table?lang=en&category=reg.reg_dem.reg_dempoar.

The data concerns population density levels by NUTS2 and year, from 2000 to 2017.

Median age. Source: Eurostat - DEMS. link:

- https://ec.europa.eu/eurostat/databrowser/view/demo_r_d3dens/default/table?lang=en&category=reg.reg_dem.reg_dempoar.

The data concerns the median age of the population by NUTS2 and year, from 2000 to 2017.

Population by educational attainment. Source: Eurostat - LFS. link:

- https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfsd2pop/default/table?lang=en&category=reg.reg_lmk.lfst_r_lfpop.

The data concerns population by educational attainment levels by NUTS2 and year, from 2000 to 2017. The levels are the following: less than primary, primary and lower secondary education (ISCED 2011 levels 0-2); upper secondary and post-secondary non-tertiary education (ISCED 2011 levels 3 and 4); tertiary education (ISCED 2011 levels 5-8).

B.5 Automation exposure data

Data on automation exposure comes from Anelli et al. (2021). Anelli et al. (2021) estimate regional time-varying exposure to automation as $Robot\ Exp_{r,t} = \sum_j \frac{L_{rj,t_0}}{L_{cj,t_0}} \cdot \frac{\Delta Robot_{cj,t_k}}{L_{r,t_0}}$, where $\Delta Robot_{cj,t_k}$ is the change in the operational stock of industrial robots between year t and $t - k$.

B.6 Brown employment data

To measure regional brown exposure, we use 2-digit selected manufacturing and mining employment levels at the NUTS2, at baseline (average between 2000 and 2003). The 2-digit manufacturing sectors are: 4 - manufacture of basic metals; 25 - manufacture of fabricated metal products; 21 - manufacture of basic pharmaceutical products;

20 - manufacture of chemicals and chemical products; 23 - manufacture of other non-metallic mineral products; 19 - manufacture of coke and refined petroleum products. These sectors are identified as polluting from Table A2. The 2-digit mining sectors are: 05 - mining of coal and lignite; 06 - Extraction of crude petroleum and natural gas; 07 - mining of metal ores; 08 - other mining and quarrying. The 2-digit mining sector 09 - mining support service activities are not included. Then, regional brown employment is computed as $BP_{r,t_0} = \sum_j \frac{L_{r,j=poll,t_0}}{L_{r,t_0}}$. We then measure elevated regional brown exposure by identifying those NUTS2 regions that have values of this ratio above the 75th percentile.

Table B1: Green goods list

Code	Label
16101010	Railway or tramway sleepers (cross-ties) of wood, not impregnated
16101300	Railway or tramway sleepers (cross-ties) of wood, not impregnated
16103200	Railway or tramway sleepers (cross-ties) of impregnated wood
20595990	Biofuels (diesel substitute), other chemical products, n.e.c.
20595997	Biofuels (diesel substitute)
23121330	Multiple-walled insulating units of glass
23991930	Mixtures and articles of heat/sound-insulating materials n.e.c.
24107500	Railway material (of steel)
24333000	Structures, solely or principally of iron or steel sheet comprising two walls of profil...
25112200	Iron or steel towers and lattice masts
25301150	Vapour generating boilers (including hybrid boilers) (excluding central heating hot wat...
25301230	Auxiliary plant for use with boilers of HS 8402 or 8403
25301330	Parts of vapour generating boilers and super-heater water boilers
25302100	Nuclear reactors
25302200	Parts of nuclear reactors
25991131	Sanitary ware and parts of sanitary ware of iron or steel
25992910	Railway or tramway track fixtures and fittings and parts thereof
26112220	Semiconductor light emitting diodes (LEDs)
26112240	Photosensitive semiconductor devices; solar cells, photo-diodes, photo-transistors, etc.
26114070	Parts of diodes, transistors and similar semiconductor devices, photosensitive semicond...
26405190	LED backlight modules for LCDs of headings 8525 to 8528 (excl. for computer monitors)
26511200	Theodolites and tachymetres (tachometers); other surveying, hydrographic, oceanographic...
26511215	Electronic rangefinders, theodolites, tacheometers and photogrammetrical instruments an...
26511235	Electronic instruments and apparatus for meteorological, hydrological and geophysical p...
26511239	Other electronic instruments, n.e.c.
26511270	Surveying (including photogrammetrical surveying), hydrographic, oceanographic, hydrolo...
26511280	Non electronic surveying (including photogrammatrical surveying), hydrographic, oceanog...
26514100	Instruments and apparatus for measuring or detecting ionising radiations
26514200	Cathode-ray oscilloscopes and cathode-ray oscillographs
26514300	Instruments for measuring electrical quantities without a recording device
26514310	Multimeters without recording device
26514330	Electronic instruments and apparatus for measuring or checking voltage, current, resist...
26514355	Voltmeters without recording device
26514359	Non-electronic instruments and apparatus, for measuring or checking voltage, current, r...

Continued on next page

Table B1 – continued from previous page

Code	Label
26514530	Instruments and apparatus, with a recording device, for measuring or checking electric ...
26514555	Electronic instruments and apparatus, without a recording device, for measuring or chec...
26514559	Non-electronic instruments and apparatus, without a recording device, for measuring or ...
26515110	Thermometers, liquid-filled, for direct reading, not combined with other instruments (e...
26515135	Electronic thermometers and pyrometers, not combined with other instruments (excluding ...
26515139	Thermometers, not combined with other instruments and not liquid filled, n.e.c.
26515235	Electronic flow meters (excluding supply meters, hydrometric paddle-wheels)
26515239	Electronic instruments and apparatus for measuring or checking the level of liquids
26515255	Non-electronic flow meters (excluding supply meters, hydrometric paddle-wheels)
26515313	Electronic gas or smoke analysers
26515319	Non-electronic gas or smoke analysers
26515330	Spectrometers, spectrophotometers... using optical radiations
26515350	Instruments and apparatus using optical radiations, n.e.c.
26515381	Electronic ph and rh meters, other apparatus for measuring conductivity and electrochem...
26515390	Other instruments and apparatus for physical or chemical analysis n.e.c.
26516350	Liquid supply or production meters (including calibrated) (excluding pumps)
26516370	Electricity supply or production meters (including calibrated) (excluding voltmeters, a...
26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus
26516620	Test benches
26516650	Electronic instruments, appliances and machines for measuring or checking geometrical q...
26516683	Other instruments, appliances,... for measuring or checking geometrical quantities
26516689	Non-electronic measuring machines and instruments (excluding test benches, optical inst...
26517015	Electronic thermostats
26517019	Non-electronic thermostats
26518200	Parts and accessories for the goods of 26.51.12, 26.51.32, 26.51.33, 26.51.4 and 26.51....
26518550	Parts and accessories for automatic regulating or controlling instruments and apparatus
26702450	Other instruments and apparatus using optical radiation (UV, visible, IR)
26702490	Exposure meters, stroboscopes, optical instruments, appliances and machines for inspect...
27111010	Electric motors of an output $\leq 37,5$ W (including synchronous motors ≤ 18 W, univers...
27111095	Photovoltaic DC generators of an output not exceeding 50 W
27111096	Photovoltaic DC generators of an output exceeding 50 W
27112680	Photovoltaic AC generators
27115023	Polycrystalline semiconductors
27116110	Parts suitable for use solely or principally with electric motors and generators, elect...
27123130	Numerical control panels with built-in automatic data-processing machine for a voltage ...
27123150	Programmable memory controllers for a voltage ≤ 1 kV
27123170	Other bases for electric control, distribution of electricity, voltage $\leq 1\ 000$ V
27201100	Primary cells and primary batteries
27201110	Manganese dioxide cells and batteries, alkaline, in the form of cylindrical cells (excl...
27201115	Other manganese dioxide cells and batteries, alkaline (excl. spent, and cylindrical cells)
27201120	Manganese dioxide cells and batteries, non-alkaline, in the form of cylindrical cells (...)
27201125	Other manganese dioxide cells and batteries, non-alkaline (excl. spent, and cylindrical...
27201130	Mercuric oxide primary cells and primary batteries (excl. spent)
27201140	Silver oxide primary cells and primary batteries (excl. spent)

Continued on next page

Table B1 – continued from previous page

Code	Label
27201150	Lithium primary cells and primary batteries, in the form of cylindrical cells (excl. spent)
27201155	Lithium primary cells and primary batteries, in the form of button cells (excl. spent)
27201160	Lithium primary cells and primary batteries (excl. spent, and in the form of cylindrical cells)
27201170	Air-zinc primary cells and primary batteries (excl. spent)
27201175	Dry zinc-carbon primary batteries of a voltage of $\geq 5,5$ V but $\leq 6,5$ V (excl. spent)
27201190	Other primary cells and primary batteries, electric (excl. spent, dry zinc-carbon batteries)
27201200	Parts of primary cells and primary batteries (excluding battery carbons, for rechargeable)
27202300	Nickel-cadmium, nickel metal hydride, lithium-ion, lithium polymer, nickel-iron and other
27202350	Lithium-ion accumulators (excl. spent)
27401250	Tungsten halogen filament lamps for motorcycles and motor vehicles (excluding ultraviolet)
27401293	Tungsten halogen filament lamps, for a voltage $> \hat{A}$ 100 V (excluding ultraviolet and infrared)
27401295	Tungsten halogen filament lamps for a voltage $\leq \hat{A}$ 100 V (excluding ultraviolet and infrared)
27401510	Fluorescent hot cathode discharge lamps, with double ended cap (excluding ultraviolet lamps)
27401530	Fluorescent hot cathode discharge lamps (excluding ultraviolet lamps, with double ended cap)
27402200	Electric table, desk, bedside or floor-standing lamps
27403090	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for general lighting
27403200	Lighting sets for Christmas trees
27403930	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for general lighting
27512690	Other electric space heaters
27521400	Non-electric instantaneous or storage water heaters
27902050	Indicator panels incorporating light emitting diodes (LED)
27902060	Light-emitting diode (LED) modules and lamps
27904200	Fuel cells
279900Z1	Parts suitable for use solely or principally with electric motors and generators, electric
28112130	Steam turbines and other vapour turbines (excluding for electricity generation)
28112150	Steam turbines for electricity generation
28112160	Steam turbines and other vapour turbines
28112200	Hydraulic turbines and water wheels
28112400	Generating sets, wind-powered
28113100	Parts for steam turbines and other vapour turbines
28113200	Parts for hydraulic turbines and water wheels (including regulators)
28211354	Electric furnaces and ovens (excluding induction- and resistance-heated); equipment for heating
28211362	Dielectric furnaces and ovens, electron beam furnaces, plasma and vacuum arc furnaces, ...
28211470	Parts for industrial or laboratory electric, induction or dielectric furnaces and ovens...
28221130	Pulley tackle and hoists powered by an electric motor (excluding of the kind used for raising and lowering)
28221250	Winches and capstans powered by an electric motor or internal combustion piston engines...
28221513	Self-propelled works trucks fitted with lifting or handling equipment, powered by an electric motor
28221515	Self-propelled works trucks fitted with lifting or handling equipment, powered by an electric motor
28241150	Grinders, sanders and planers, for working in the hand, with self-contained electric motor
28241185	Electromechanical hand tools, with self-contained electric motor operating with an external power source
28251130	Heat exchange units
28251380	Heat pumps other than air conditioning machines of HS 8415
28251410	Machinery and apparatus for filtering or purifying air (excluding intake filters for internal combustion engines)
28251420	Machinery and apparatus for filtering or purifying gases by a liquid process (excluding for internal combustion engines)

Continued on next page

Table B1 – continued from previous page

Code	Label
28251430	Machinery and apparatus for filtering and purifying gases (other than air and excluding...
28251431	Machinery and apparatus for filtering and purifying gases (other than air and excluding...
28251440	Machinery and apparatus for filtering or purifying gases by catalytic process (excludin...
28251441	Machinery and apparatus for filtering or purifying gases by catalytic process (excludin...
28251442	Catalytic converters or particulate filters, whether or not combined, for purifying or ...
28251450	Machinery and apparatus for filtering and purifying gases with stainless steel housing,...
28251470	Machinery and apparatus for filtering or purifying gases including for filtering dust f...
28253070	Parts of refrigerating or freezing equipment and heat pumps, n.e.s.
28291100	Producer gas or water gas generators; acetylene gas generators and the like; distilling...
28291230	Machinery and apparatus for filtering or purifying water
28291270	Machinery and apparatus for solid-liquid separation/ purification excluding for water a...
28298250	Parts for filtering and purifying machinery and apparatus, for liquids or gases (exclud...
28304010	Electric mowers for lawns, parks, golf courses or sports grounds
28992020	Machines and apparatus used solely or principally for the manufacture of semiconductor ...
28992060	Machines and apparatus used solely or principally for the manufacture of flat panel dis...
28993945	Machines and apparatus used solely or principally for (a) the manufacture or repair of ...
29102410	Motor vehicles, with both spark-ignition or compression-ignition internal combustion re...
29102430	Motor vehicles, with both spark-ignition or compression-ignition internal combustion re...
29102450	Motor vehicles, with only electric motor for propulsion
29104142	Motor vehicles for the transport of goods with both compression-ignition internal combu...
29104212	Motor vehicles for the transport of goods with both spark-ignition internal combustion ...
29104213	Motor vehicles for the transport of goods with only electric motor for propulsion
29104311	Road tractors for semi-trailers with both compression-ignition internal combustion pist...
29104312	Road tractors for semi-trailers with both spark-ignition internal combustion piston eng...
29104313	Road tractors for semi-trailers with only electric motor for propulsion
29105200	Motor vehicles specially designed for travelling on snow, golf cars and similar vehicles
29312310	Electrical or battery operated lighting or visual signalling of a kind used on bicycles
30201100	Rail locomotives powered from an external source of electricity
30201200	Diesel-electric locomotives
30201300	Other rail locomotives; locomotive tenders
30202000	Self-propelled railway or tramway coaches, vans and trucks, except maintenance or servi...
30203100	Railway or tramway maintenance or service vehicles (including workshops, cranes, ballas...
30203200	Rail/tramway passenger coaches; luggage vans, post office coaches and other special pur...
30203300	Railway or tramway goods vans and wagons, not self-propelled
30204030	Parts of locomotives or rolling-stock
30204050	Mechanical or electromechanical signalling, safety or traffic control equipment for roa...
30204070	Fixtures and fittings and mechanical signalling, safety or traffic control equipment fo...
30209100	Reconditioning of railway and tramway locomotives and rolling-stock
30921000	Bicycles and other cycles (including delivery tricycles), non-motorised
30921030	Non-motorized bicycles and other cycles, without ball bearings (including delivery tric...
30921050	Non-motorized bicycles and other cycles with ball bearings (including delivery tricycles)
30923010	Frames and forks, for bicycles
30923030	Parts of frames, front forks, brakes, coaster braking hubs, hub brakes, pedals crank-ge...
30923060	Parts and accessories of bicycles and other cycles, not motorised (excl. frames, front ...

Continued on next page

Table B1 – continued from previous page

Code	Label
30923070	Parts and accessories for invalid carriages
30923090	Other parts and accessories of bicycles and other cycles, not motorised
33141120	Repair and maintenance of electric motors, generators and transformers
33141150	Repair and maintenance of electricity distribution and control apparatus
33141900	Repair and maintenance of electrical equipment (excluding electricity distribution and ...
33171100	Repair and maintenance of railway and tramway locomotives and rolling-stock and of mech...
33205020	Installation of electric motors, generators and transformers
33205050	Installation of electricity distribution and control apparatus
33205090	Installation of other electrical equipment, excluding electrical signalling equipment f...

Table B2: NUTS2 regions in the sample list

Code	Label
AT11	AT - Burgenland
AT12	AT - Niederösterreich
AT13	AT - Wien
AT21	AT - Kärnten
AT22	AT - Steiermark
AT31	AT - Oberösterreich
AT32	AT - Salzburg
AT33	AT - Tirol
AT34	AT - Vorarlberg
BE10	BE - Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest
BE21	BE - Prov. Antwerpen
BE22	BE - Prov. Limburg (BE)
BE23	BE - Prov. Oost-Vlaanderen
BE24	BE - Prov. Vlaams-Brabant
BE25	BE - Prov. West-Vlaanderen
BE31	BE - Prov. Brabant wallon
BE32	BE - Prov. Hainaut
BE33	BE - Prov. Liège
BE34	BE - Prov. Luxembourg (BE)
BE35	BE - Prov. Namur
BG31	BG - Severozapaden
BG32	BG - Severen tsentralen
BG33	BG - Severoiztochen
BG34	BG - Yugoiztochen
BG41	BG - Yugozapaden
BG42	BG - Yuzhen tsentralen
CY00	CY - Kýpros
CZ01	CZ - Praha
CZ02	CZ - Střední Čechy
CZ03	CZ - Jihozápad

Continued on next page

Table B2 – continued from previous page

Code	Label
CZ04	CZ - Severozápad
CZ05	CZ - Severovýchod
CZ06	CZ - Jihovýchod
CZ07	CZ - Střední Morava
CZ08	CZ - Moravskoslezsko
DE11	DE - Stuttgart
DE12	DE - Karlsruhe
DE13	DE - Freiburg
DE14	DE - Tübingen
DE21	DE - Oberbayern
DE22	DE - Niederbayern
DE23	DE - Oberpfalz
DE24	DE - Oberfranken
DE25	DE - Mittelfranken
DE26	DE - Unterfranken
DE27	DE - Schwaben
DE30	DE - Berlin
DE40	DE - Brandenburg
DE50	DE - Bremen
DE60	DE - Hamburg
DE71	DE - Darmstadt
DE72	DE - Gießen
DE73	DE - Kassel
DE80	DE - Mecklenburg-Vorpommern
DE91	DE - Braunschweig
DE92	DE - Hannover
DE93	DE - Lüneburg
DE94	DE - Weser-Ems
DEA1	DE - Düsseldorf
DEA2	DE - Köln
DEA3	DE - Münster
DEA4	DE - Detmold
DEA5	DE - Arnsberg
DEB1	DE - Koblenz
DEB2	DE - Trier
DEB3	DE - Rheinhessen-Pfalz
DEC0	DE - Saarland
DED2	DE - Dresden
DED4	DE - Chemnitz
DED5	DE - Leipzig
DEE0	DE - Sachsen-Anhalt
DEF0	DE - Schleswig-Holstein
DEG0	DE - Thüringen
DK01	DK - Hovedstaden

Continued on next page

Table B2 – continued from previous page

Code	Label
DK02	DK - Sjælland
DK03	DK - Syddanmark
DK04	DK - Midtjylland
DK05	DK - Nordjylland
EL30	EL - Attiki
EL41	EL - Voreio Aigaio
EL42	EL - Notio Aigaio
EL43	EL - Kriti
EL51	EL - Anatoliki Makedonia, Thraki
EL52	EL - Kentriki Makedonia
EL53	EL - Dytiki Makedonia
EL54	EL - Ipeiros
EL61	EL - Thessalia
EL62	EL - Ionia Nisia
EL63	EL - Dytiki Ellada
EL64	EL - Sterea Ellada
EL65	EL - Peloponnisos
ES11	ES - Galicia
ES12	ES - Principado de Asturias
ES13	ES - Cantabria
ES21	ES - País Vasco
ES22	ES - Comunidad Foral de Navarra
ES23	ES - La Rioja
ES24	ES - Aragón
ES30	ES - Comunidad de Madrid
ES41	ES - Castilla y León
ES42	ES - Castilla-La Mancha
ES43	ES - Extremadura
ES51	ES - Cataluña
ES52	ES - Comunitat Valenciana
ES53	ES - Illes Balears
ES61	ES - Andalucía
ES62	ES - Región de Murcia
ES63	ES - Ciudad de Ceuta
ES64	ES - Ciudad de Melilla
FI19	FI - Länsi-Suomi
FI1B	FI - Etelä-Suomi
FI1C	FI - Etelä-Suomi
FI1D	FI - Itä-Suomi
FI20	FI - Åland
FR10	FR - Ile de France
FRB0	FR - Centre (FR)
FRC1	FR - Bourgogne
FRC2	FR - Franche-Comté

Continued on next page

Table B2 – continued from previous page

Code	Label
FRD1	FR - Basse-Normandie
FRD2	FR - Haute-Normandie
FRE1	FR - Nord-Pas-de-Calais
FRE2	FR - Picardie
FRF1	FR - Alsace
FRF2	FR - Champagne-Ardenne
FRF3	FR - Lorraine
FRG0	FR - Pays de la Loire
FRH0	FR - Bretagne
FRI1	FR - Aquitaine
FRI2	FR - Limousin
FRI3	FR - Poitou-Charentes
FRJ1	FR - Languedoc-Roussillon
FRJ2	FR - Midi-Pyrénées
FRK1	FR - Auvergne
FRK2	FR - Rhône-Alpes
FRL0	FR - Provence-Alpes-Côte d'Azur
FRM0	FR - Corse
HR03	HR - Jadranska Hrvatska
HR04	HR - Kontinentalna Hrvatska
HU11	HU - Közép-Magyarország
HU12	HU - Közép-Magyarország
HU21	HU - Közép-Dunántúl
HU22	HU - Nyugat-Dunántúl
HU23	HU - Dél-Dunántúl
HU31	HU - Észak-Magyarország
HU32	HU - Észak-Alföld
HU33	HU - Dél-Alföld
IE04	IE - Border, Midland and Western
IE05	IE - Southern and Eastern
IE06	IE - Southern and Eastern
IS00	IS - Iceland
ITC1	IT - Piemonte
ITC2	IT - Valle d'Aosta/Vallée d'Aoste
ITC3	IT - Liguria
ITC4	IT - Lombardia
ITF1	IT - Abruzzo
ITF2	IT - Molise
ITF3	IT - Campania
ITF4	IT - Puglia
ITF5	IT - Basilicata
ITF6	IT - Calabria
ITG1	IT - Sicilia
ITG2	IT - Sardegna

Continued on next page

Table B2 – continued from previous page

Code	Label
ITH1	IT - Provincia Autonoma Bolzano/Bozen
ITH2	IT - Provincia Autonoma Trento
ITH3	IT - Veneto
ITH4	IT - Friuli-Venezia Giulia
ITH5	IT - Emilia-Romagna
ITI1	IT - Toscana
ITI2	IT - Umbria
ITI3	IT - Marche
ITI4	IT - Lazio
LU00	LU - Luxembourg
LV00	LV - Latvia
MT00	MT - Malta
NL11	NL - Groningen
NL12	NL - Friesland (NL)
NL13	NL - Drenthe
NL21	NL - Overijssel
NL22	NL - Gelderland
NL23	NL - Flevoland
NL31	NL - Utrecht
NL32	NL - Noord-Holland
NL33	NL - Zuid-Holland
NL34	NL - Zeeland
NL41	NL - Noord-Brabant
NL42	NL - Limburg (NL)
NO01	NO - Oslo og Akershus
NO02	NO - Innlandet
NO03	NO - Sør-Østlandet
NO04	NO - Agder og Rogaland
NO05	NO - Vestlandet
NO06	NO - Trøndelag
NO07	NO - Nord-Norge
PL21	PL - Małopolskie
PL22	PL - Śląskie
PL41	PL - Wielkopolskie
PL42	PL - Zachodniopomorskie
PL43	PL - Lubuskie
PL51	PL - Dolnośląskie
PL52	PL - Opolskie
PL61	PL - Kujawsko-pomorskie
PL62	PL - Warmińsko-mazurskie
PL63	PL - Pomorskie
PL71	PL - Łódzkie
PL72	PL - Świętokrzyskie
PL81	PL - Lubelskie

Continued on next page

Table B2 – continued from previous page

Code	Label
PL82	PL - Podkarpackie
PL84	PL - Podlaskie
PL91	PL - Mazowieckie
PL92	PL - Mazowieckie
PT11	PT - Norte
PT15	PT - Algarve
PT16	PT - Centro (PT)
PT17	PT - Área Metropolitana de Lisboa
PT18	PT - Alentejo
RO11	RO - Nord-Vest
RO12	RO - Centru
RO21	RO - Nord-Est
RO22	RO - Sud-Est
RO31	RO - Sud-Muntenia
RO32	RO - Bucureşti-Ilfov
RO41	RO - Sud-Vest Oltenia
RO42	RO - Vest
SE11	SE - Stockholm
SE12	SE - Östra Mellansverige
SE21	SE - Småland med öarna
SE22	SE - Sydsverige
SE23	SE - Västsverige
SE31	SE - Norra Mellansverige
SE32	SE - Mellersta Norrland
SE33	SE - Övre Norrland
SI03	SI - Vzhodna Slovenija
SI04	SI - Zahodna Slovenija
SK01	SK - Bratislavský kraj
SK02	SK - Západné Slovensko
SK03	SK - Stredné Slovensko
SK04	SK - Východné Slovensko
UKC1	UK - Tees Valley and Durham
UKC2	UK - Northumberland and Tyne and Wear
UKD1	UK - Cumbria
UKD3	UK - Greater Manchester
UKD4	UK - Lancashire
UKD6	UK - Cheshire
UKD7	UK - Merseyside
UKE1	UK - East Yorkshire and Northern Lincolnshire
UKE2	UK - North Yorkshire
UKE3	UK - South Yorkshire
UKE4	UK - West Yorkshire
UKF1	UK - Derbyshire and Nottinghamshire
UKF2	UK - Leicestershire, Rutland and Northamptonshire

Continued on next page

Table B2 – continued from previous page

Code	Label
UKF3	UK - Lincolnshire
UKG1	UK - Herefordshire, Worcestershire and Warwickshire
UKG2	UK - Shropshire and Staffordshire
UKG3	UK - West Midlands
UKH1	UK - East Anglia
UKH2	UK - Bedfordshire and Hertfordshire
UKH3	UK - Essex
UKI3	UK - Inner London
UKI4	UK - Inner London
UKI5	UK - Outer London
UKI6	UK - Outer London
UKI7	UK - Outer London
UKJ1	UK - Berkshire, Buckinghamshire and Oxfordshire
UKJ2	UK - Surrey, East and West Sussex
UKJ3	UK - Hampshire and Isle of Wight
UKJ4	UK - Kent
UKK1	UK - Gloucestershire, Wiltshire and Bristol/Bath area
UKK2	UK - Dorset and Somerset
UKK3	UK - Cornwall and Isles of Scilly
UKK4	UK - Devon
UKL1	UK - West Wales and The Valleys
UKL2	UK - East Wales
UKM5	UK - North Eastern Scotland
UKM6	UK - Highlands and Islands
UKM7	UK - Eastern Scotland
UKM8	UK - South Western Scotland
UKM9	UK - South Western Scotland
UKN0	UK - Northern Ireland (UK)



Skills for labour markets in the digital and green transition

SkiLMeeT is a research project carried out by eight research institutions, exploring how the digital and green transformation of European economies are changing the demand for skills. We analyse the scope of skills shortages and mismatches, identify their drivers and propose innovative ways to reduce skills gaps.

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