

Emerging skills and wage gaps in the low-carbon transition: evidence from online job vacancy data

Aurélien Saussay^{*†} Misato Sato^{*} Francesco Vona^{‡§}
Layla O’Kane[¶]

September 30, 2025

Abstract

Standard classifications obscure which jobs directly drive emissions cuts. Using U.S. online vacancies data, we develop a transparent, skill-based approach that identifies low-carbon roles within occupations, leveraging NLP and text linked to established green classifications. We show that, even within the same occupation and firm, low-carbon jobs systematically demand more, and more diverse, skills than non-low-carbon jobs. Within-occupation differences account for much of the overall gap, implying occupation-level studies understate it. The transition thus requires substantial retraining within existing occupations, even if not biased towards high-skilled workers. Reskilling needs are highly occupation-specific. Returns to skill complexity are higher in low-carbon roles, yet the green wage premium is positive but modest and declining after controlling for occupation and firm heterogeneity. Low-carbon jobs are more geographically dispersed than high-carbon ones but more prevalent in wealthier areas, implying reallocation frictions and equity concerns. Our evidence supports targeted reskilling policies to support a just transition.

Keywords: Green and low-carbon jobs, green skills, task-based approach, reallocation costs, low-carbon transition

JEL codes: Q52, Q58, Q4, Q41, H23

^{*}London School of Economics and Political Science, Houghton Street, Grantham Research Institute, London WC2A 2AE, U.K. (email:a.saussay@lse.ac.uk) (email:m.sato1@lse.ac.uk)

[†]Sciences Po, OFCE, 10 place de Catalogne, Paris, 75014, France

[‡]University of Milan, Via Festa del Perdono 7 - 20122, Milano, Italy. (email:francesco.vona@unimi.it)

[§]FEEM, Corso Magenta 63 - 20123, Milano, Italy

[¶]Lightcast (email: layla.okane@lightcast.io)

1 Introduction

In parallel with the ongoing technological advancements in digitization and artificial intelligence (Autor et al., 2003; Acemoglu and Autor, 2011), the energy transition is reshaping labor markets by reallocating workers toward low-carbon activities while potentially displacing skills used in high-carbon activities. The anticipation of significant job reallocations under ambitious decarbonization scenarios (Hafstead and Williams III, 2018; Castellanos and Heutel, 2024) and concerns over skill and spatial mismatches that may jeopardize climate goals, compounded by persistent opposition from fossil fuel lobbies citing job losses (Vona, 2019; Weber, 2020), have spurred policymakers and researchers to better understand labor market adjustments to the low-carbon transition (IMF, 2022; OECD, 2023; EBRD, 2023). A key aspect for political acceptability is the quality of low-carbon jobs created in exchange of the high-carbon jobs destroyed, especially in terms of wage premia and skill requirements (Meyer, 2022).

However, a major barrier to understanding the characteristics of low-carbon jobs is the lack of reliable data (Dierdorff et al., 2009; Consoli et al., 2016; Vona et al., 2018). Low-carbon jobs – defined as those that directly contribute to decarbonizing the economy – are not adequately captured in standard occupational classifications, which are too infrequently updated to reflect the emergence of new jobs driven by technological change. These classifications also fail to distinguish between high- and low-carbon roles within the same occupation. For example, the category Automotive Service Technicians and Mechanics (SOC 49-3023) includes both electric vehicle and combustion engine car repairers, making it difficult to assess the unique skill and wage profiles of low-carbon jobs.

This paper addresses these limitations by shifting from an occupation-level comparison to a job-level perspective, offering the first broad assessment of skill and wage gaps as well as spatial barriers associated with the low-carbon transition. To identify low-carbon jobs within standard occupational groups, we build on a growing body of literature in labor economics using online job vacancy (OJV) data and their skill content to measure worker exposure to emerging technologies, such as automation and routine-biased technological change (Deming and Kahn, 2018; Atalay et al., 2020), Artificial Intelligence (Acemoglu et al., 2022; Alekseeva et al., 2021) and general macroeconomic shocks (Hershbein and Kahn, 2018a; Chetty et al., 2024). Our primary contribution is to extend and adapt this methodology to the low-carbon technological change context by leveraging a near universe of U.S. online job vacancy data from Lightcast spanning 2010-2019.

We develop a novel, data-driven methodology, applying advanced natural language processing (NLP) techniques to textual data from well-established green classifications, i.e. the U.S. Occupational Information Network (O*NET) green tasks, CPC green patent classes and green products from PRODCOM, to identify the skills most semantically rel-

evant to decarbonization in the Lightcast dataset. This process isolates 389 low-carbon skills* and identifies approximately 1.8 million job postings containing them, from a total of 200 million postings. A key advantage of our approach is its ability to distinguish between low-carbon and non-low-carbon roles within narrow occupational categories. For example, we can isolate Renewable Grid Integration Engineers among Electrical Engineers, and Wind Turbine Service Technicians among Installation, Maintenance, and Repair Occupations, while excluding roles within low-carbon sectors or firms that do not directly contribute to decarbonization such as Office and Administrative Support Occupations. The resulting sample of low-carbon jobs goes beyond the energy sector, which was the focus of previous studies (Curtis and Marinescu, 2023; Fabra et al., 2023), and spans across a wide range of sectors, including construction and manufacturing, which are likely to have larger effects on local job creation in the energy transition.[†] To prove the robustness of our results to the key methodological choices, we cross-validate our method through a comparison with task-based measures of green jobs (Vona et al., 2019; Elliott et al., 2024) and extensive sensitivity checks.

Our skill-based methodology allows us to qualify and revisits several facts about green jobs that are often taken for granted in the policy debate (OECD and CEDEFOP, 2014; Kruse et al., 2017; Tomer and George, 2021; IMF, 2022; OECD, 2024). First, the share of green jobs is smaller than previously thought. Green job shares have been estimated to be in the range of 2-3% of total employment in studies using the task based approach with occupation level data (Vona et al., 2019; Popp et al., 2021), or data on green production (Becker and Shadbegian, 2009; Elliott and Lindley, 2017; Frattini et al., 2024), while those that bypass the re-weighting of employment by green task intensity report shares as high as 20% (OECD, 2024; Bowen et al., 2018; Valero et al., 2021). Our methodology accurately isolates low-carbon jobs within occupations and estimates that the shares of low-carbon employment have been around 1%, suggesting previous estimates exaggerated the job creation effect of the green transition so far.

Second, we find that low-carbon job creation is more prevalent in low-skilled occupations than high-skilled ones, thus questioning the common belief that the green transition, like the parallel digital transition and globalization, will be biased against low-skilled workers. Indeed, although job destruction of climate policies may be concentrated among low-skilled workers (Marin and Vona, 2019; Yip, 2018), the very same workers may find new employment opportunities in green activities. Importantly, this does not imply that reskilling is not important for low-carbon technologies. Indeed, we find that low-carbon

*The list of identified low-carbon skills is made open source for transparency and as a resource for future research.

[†]For instance, Popp et al. (2021) show that the largest effects of the Obama green recovery package were on construction workers. Knowledge-intensive engineering services and manufacturing are two other sectors that provide key technologies for decarbonization but were under-investigated in previous studies on green activities, with a few exceptions (Fankhauser et al., 2013; Frattini et al., 2024).

jobs have more complex and diverse skill needs than similar jobs *within* the same occupation. We also find that re-skilling needs are highly idiosyncratic and occupation-specific, requiring a more nuanced approach to retraining compared to the more simple solutions being advocated in policy circles (Strietska-Illina et al., 2012; OECD and CEDEFOP, 2014; OECD, 2024).

Third, *within-occupation* skill gaps are larger than previously thought. We show that the skill gap within narrow occupations significantly contributes to the overall differences in skill requirements between low-carbon and non-low-carbon roles, suggesting previous estimates that considered only the between-occupation variation were underestimated (Vona et al., 2018; Zaussinger et al., 2025). We also show that green skill gaps are highly idiosyncratic and occupation-specific, requiring either specializing into core occupational skills or diversifying towards new ones. Moreover, while across the board technical and managerial skills emerge as the most important skills for low-carbon occupations, social, IT and cognitive skills are also in higher demand in some green roles.

Fourth, the wage premium for low-carbon jobs are smaller than previously thought (Antoni et al., 2015; Bluedorn et al., 2023; Vona et al., 2019; Curtis and Marinescu, 2023; Kuai et al., 2025; Whittard et al., 2025), despite the higher skill complexity demanded in low-carbon vacancies. Once controlling for 2-digit occupational dummies (a proxy of broad occupational characteristics) and firm fixed effects (a proxy of rent and productivity differentials), the low-carbon wage premia are modest and decline over time. Particularly, our results highlight that firm fixed effects account for a large fraction of what was previously thought to be a large green wage premium, consistent with the literature on the role of firm wage differentials as a key and growing determinant of wage inequality (Abowd et al., 1999; Card et al., 2013; Song et al., 2019). The modest low-carbon wage premium contrasts with high premium for high-carbon jobs in the same occupational groups, indicating a potential attractiveness gap that may deter talented workers from choosing a career in low-carbon activities.

Fifth, concentrating on low-skilled workers, who face higher risk of long-term unemployment and social exclusion and thus the main target of so-called just transition policies, we show that emerging low-carbon jobs tend to be more spatially dispersed than declining high-carbon ones. Nonetheless, we find positive spatial correlation between high-carbon and low-carbon jobs in line with previous work examining jobs in renewable energy (Curtis and Marinescu, 2023). Although this suggests that U.S. fossil fuel communities may attract some green job creation, since low-carbon vacancies are more concentrated in wealthier areas, the green transition could also exacerbate existing regional inequalities (Popp et al., 2021; Bluedorn et al., 2023).

Our contributions are three fold. First, we address the lack of a universal and operational

definition of low-carbon jobs, a major obstacle to rigorous research on the labor market effects of the low-carbon transition. Definitions of what qualifies as “low-carbon” are often contentious, and such debates can stall progress in both policy and public discourse. Our approach seeks to move beyond this impasse by developing a transparent, replicable and flexible data-driven method that avoids subjective choices in isolating jobs directly contributing to decarbonization. We do so by applying NLP techniques to rich text data from well-established green classifications and OJV data. In this way, we contribute both to the emerging research using OJV data to study the green transition (Curtis and Marinescu, 2022; Bone et al., 2025) and to the broader labor economics literature on the impact of new technologies using OJV data (Deming and Noray, 2020; Acemoglu et al., 2020), which has not previously applied these data to classify low-carbon jobs.

Second, we depart from previous research on green jobs (Vona et al., 2018; Bowen et al., 2018; Vona et al., 2019; Bluedorn et al., 2023; Elliott et al., 2024) by exploiting within-occupation and within-firm variation in the data, thereby demonstrating the value of using granular, job-level analysis. This enables us to characterize reskilling needs more precisely, and provide more reliable estimates of wage premia arising from low-carbon-related technological change, particularly within the most exposed occupational groups. Controlling for unobserved heterogeneity at both the occupation and firm level is essential for constructing reliable counterfactuals, comparing low-carbon jobs to similar non-low-carbon jobs (within-occupation) and isolating the firm-level component of the low-carbon wage premium. This approach is especially valuable outside the U.S. context, where lack of official data on the task content of occupations and coarse occupational classifications, such as those in the UK and Europe, severely constrain occupational-level analysis.

Third, our coverage of low-carbon jobs across all occupations and sectors allows us to examine the extent to which the low-carbon transition can be considered “just” in terms of benefiting distressed regions and manual workers who have been left behind by other structural transformations, such as globalization and automation (Iammarino et al., 2019; Autor et al., 2021; Hanson, 2023).[‡] In doing so, our work directly addresses the concerns of workers and communities in high-carbon industries, thereby helping to enhance the political acceptability of ambitious climate action.

Taken together, our transparent methodology and detailed analysis substantially improves the evidence on skills and wage gaps, providing a stronger foundation for designing comprehensive policy frameworks, e.g. green deal plans, that strategically target training programs, reskilling investments and wage insurance subsidies where they are most needed.

[‡]Previous empirical evaluations typically focus on specific polluting sectors where job destruction is likely concentrated, for instance evaluating the U.S. Clean Air Act (e.g. Greenstone, 2002; Morgenstern et al., 2002; Walker, 2011; Curtis, 2018; Walker, 2013), the effects of carbon pricing in Europe (e.g. Martin et al., 2014; Marin et al., 2018; Dechezleprêtre et al., 2023) or that of energy prices (Deschenes, 2011; Kahn and Mansur, 2013; Marin and Vona, 2019)

This paper is structured as follows. Section 2 presents the data and our methodology for identifying low-carbon jobs. Section 3 describes the evolution of U.S. low-carbon job shares. Section 4 quantifies the skill gap between low- and high-carbon jobs and generic jobs. Section 5 estimates low-carbon wage premiums. Section 6 explores spatial gaps for displaced low-skilled workers, before concluding in Section 7.

2 A skill-based approach to identifying low-carbon jobs

Given the salience of decarbonization in current policy debates, this paper focuses on “low-carbon” activities, a subset of “green” activities that specifically contribute to reducing greenhouse gas (GHG) emissions across various sectors. Unlike standard definitions of green jobs, which often encompass activities related to water, waste management, remediation, and recycling, our analysis narrows the focus to activities that directly support decarbonization. This approach not only captures efforts to reduce emissions from power generation but also extends to sectors that received substantial funding under green recovery packages, such as construction, transport and manufacturing.

Isolating low-carbon skills presents several challenges. Technologies constantly evolve, new low-carbon jobs continually emerge, and defining what qualifies as “low-carbon” can be highly contentious. To navigate this, we introduce a methodological framework that applies NLP techniques to text data from online job postings to identify low-carbon skills and jobs. Our skill-based approach offers several advantages over other methods using online job postings data to identify green skills and jobs (Curtis and Marinescu, 2022; Bone et al., 2025), especially around objectivity, coverage and scope, granularity and transparency.

First, a key methodological innovation is our data-driven approach to identifying what is relevant to “low-carbon”, leveraging text data from well-established low-carbon classifications to reduce subjectivity, rather than relying on researcher-defined keyword lists.[§] While some design choices are needed (see next section), it nonetheless has fewer degrees of freedom and avoids setting too narrow selection criteria or combining too many different criteria.[¶]

Second, using *only* semantic similarity between Lightcast skills and well-established green classification reduces the degree of freedom in the skill selection, thus making our approach more replicable. At the same time, the approach is highly flexible: by adjusting the source text, our approach can be adapted to identify green jobs in either a broad or narrowly defined set of activities.

[§]For example, in Acemoglu et al. (2022), the authors select 33 skills relating to Artificial Intelligence in footnote 13.

[¶]In Curtis and Marinescu (2023), relevant green jobs are identified through keyword searches applied to job titles, occupation categories, skills and firm names.

Third, our scope is wide and thorough than that of papers using OJV data for specific sectors such as renewable energy (Curtis and Marinescu, 2023) or electric vehicles (Curtis et al., 2023). Our focus on the whole economy allows to assess broader green skill gaps and thus be of more useful to design retraining programs for the low-carbon transition in critical sectors such as manufacturing and construction. Bone et al. (2025) also apply a skill-based approach to OJV data, relying on Lightcast’s Open Skill Taxonomy that identify 259 green skills. Our algorithm identifies a broader and arguably more relevant set of low-carbon skills, suggesting the presence of false negatives in the Lightcast taxonomy.[‡]

Fourth, while using firm-level definitions of green assumes that all roles within a clean energy company are inherently “green” (e.g. Curtis and Marinescu, 2023), we instead isolate only those job ads that specifically require low-carbon skills, enabling more accurate measurement of green skill requirements and wage gaps.

While our approach has clear advantages, it is not without limitations. Relying on extant green classifications means being constrained by their scope and boundaries and some design choices are needed. We demonstrate the credibility of these choices through comprehensive sensitivity checks and cross-validation against the task-based measure of green jobs, further supporting the robustness of our approach. This section documents in details the data sources and techniques applied.

2.1 The Lightcast online job vacancy data

Following recent studies in labor economics (e.g. Hershbein and Kahn, 2018b; Deming and Kahn, 2018; Acemoglu et al., 2022) we leverage data from Lightcast (formerly Burning Glass Technologies), which collects raw text from online job ads via web scraping of approximately 50,000 online job boards and company websites (Lancaster et al., 2021) for the U.S.. Lightcast cleans and codifies the raw text into standardized variables including skill requirements, occupational categories, wage offers, educational attainment, company names, and locations. Importantly, job ads contain rich textual information on skill requirements, which Lightcast canonicalizes into a taxonomy of over 16,000 unique skills. The resulting dataset covers approximately 200 million ads from 2010 to 2019, representing the near-universe of U.S. online jobs.

While increasingly used in research, it is important to recognize that OJV data over-represent growing firms (Davis et al., 2012) and certain occupations, such as business & financial, computer & mathematical, and education & law, while under-represent sectors, such as construction, sales & service, agriculture and transport (Tsvetkova et al., 2024). Furthermore, self-employment opportunities are not represented online. Finally, online job vacancy data capture changes in labor demand (i.e. a flow) rather than employment

[‡]Approximately 40% of skills in Lightcast’s database are not assigned to a skill cluster or family, partly explaining this gap. Additionally, our approach improves on transparency, as the Lightcast green skill classification is not fully documented.

(i.e. a stock). To mitigate these biases, we reweight low-carbon jobs using Bureau of Labor Statistics (BLS) employment shares in our analysis (see Appendix Table A.1).

2.2 Low-carbon skills selection algorithm

Our goal is to identify which of the 16,000+ Lightcast skills should be classified as “low-carbon”. Rather than relying on potentially subjective keyword lists, we develop a data-driven approach that leverages three complementary signals to maximize the identification of relevant skills while maintaining precision through a transparent and replicable algorithm. This multi-signal approach ensures that we capture the full spectrum of low-carbon skills across different contexts while avoiding false positives.

In particular, we do not simply rely on Lightcast’s own “Environment” skill category^{**}, as this would miss many relevant skills, such as those related to solar and wind power which are found in the “Energy and Utilities” category instead. One way to circumvent this problem would be to manually classify skills as low-carbon. However this would introduce considerable subjectivity, which the contentious nature of determining what qualifies as “low-carbon” makes particularly problematic.

To overcome these issues, we introduce a fully data-driven algorithm, leveraging three well-established green classifications. First, green tasks from the Occupational Information Network dataset (O*NET) is the main database used in the literature to identify green-related work (e.g. [Dierdorff et al., 2009](#); [Vona et al., 2018](#)). O*NET provides detailed task descriptions for green occupations, such as ‘Order parts, tools, or equipment needed to maintain, restore, or improve wind field operations’ and ‘Prepare or review detailed design drawings, specifications, or lists related to solar installations’. One limitation is that O*NET does not distinguish between low-carbon and general “green” tasks. Second, the climate change mitigation and adaptation patent categories (CPC Y02 patent class) provides established definitions used in the literature (e.g. [Egli et al., 2015](#); [Glachant and Dechezleprêtre, 2016](#); [Calel and Dechezleprêtre, 2016](#)).^{††} The advantage of this source is to add “low-carbon specific” keywords. Third, to ensure adequate coverage of the transport sector, we incorporate a list of trade product categories related to low-carbon transport (e.g. railways) from the PRODCOM database ([Bontadini and Vona, 2023](#)).

By combining these three complementary sources, we aim to cover the majority of activities relevant to decarbonization across different sectors of the economy.^{‡‡} In the following,

^{**}Lightcast skill categories, also called skill clusters in older versions of the Lightcast dataset, are groupings of skills that have similar functionality, can be trained together, and/or frequently appear together in job postings. For example, both the skills hydrology and meteorology belong to the skill subcategory “Earth and Space Science”, which belongs to the broader Skill category “Science and Research”.

^{††}For example, Class Y02E covers “Reduction of Greenhouse Gas Emissions Related to Energy Generation, Transmission or Distribution”.

^{‡‡}If, alternatively, the objective is to isolate only the jobs that relate to the hydrogen economy, a hydrogen-specific source text can be used e.g., the patent classification YO2E 60/3.

we outline the four steps of our algorithm. Full implementation details are provided in Appendix B.1.

Step 1: Keyword extraction from textual sources

We begin by extracting keywords that distinguish low-carbon content from generic content within each source classification. We apply a state-of-the-art keyword extraction algorithm, YAKE (Campos et al., 2020), to extract one- and two-word keywords characteristic of each item in our three textual sources (*i.e.*, each O*NET task, technology title or product description). The algorithm yields a relevance score for each keyword. We then select the keywords that appear in the green subsets of each source, and rank them by the difference between the scores they obtain in the green vs. non-green subsets^{§§}. We then plot the distribution of this difference across extracted keywords for each source (see Figure B.1). All three distributions exhibit clear nonlinearities which allow us to define thresholds specific to each source. Keywords that yield a difference in their green vs non-green relevance scores above the source-specific threshold enter our final set of low-carbon keywords. In our main threshold specification, this step yields 35 low-carbon keywords (see Table B.1), including terms such as “solar”, “climate change”, and “wind turbine”.

Step 2: Classify skills using three complementary signals

We then leverage textual analysis and the keywords obtained in the previous step to identify which of the 16,000+ Lightcast skills are low-carbon. We implement a three-pronged approach to maximize coverage, as different signals capture different kinds of evidence that a skill is genuinely low-carbon. Sensitivity to alternative cut-offs is reported for each signal in Appendix I.

Signal A: Contrastive frequency (not keyword-dependent). We compare how often each Lightcast skill appears in the green versus the non-green subsets of our three textual sources. A skill is flagged as low-carbon when it appears in the green subset but not in the non-green subset of a given source and its frequency score falls in the top quintile for that source. For the patent source, where core climate technologies frequently occur outside the Y02 class, we relax the “absent from non-green” requirement. This frequency-based signal identifies 46 low-carbon skills, such as “Smart Grid” and “Biofuels Processing”.

Signal B: Direct lexical match to low-carbon keywords. We then use our low-carbon keywords with a simple, direct string-match rule: if a Lightcast skill name is an exact match to any of the 35 low-carbon keywords from Step 1, it is flagged as low-carbon. This signal is particularly useful for avoiding false negatives for highly specific technical terms. These direct matches contribute an additional 214 low-carbon skills, such as “Solar Farm” and

^{§§}Considering a non-green score of zero if the keyword only appears in the green subset.

“Wind Turbine Construction”.

Signal C: Semantic match to low-carbon keywords. While effective, simple keyword matching can miss important connections due to vocabulary differences across sources. For example, a keyword like *wind turbine* is semantically related to the Lightcast skill “Clean Energy” even though they share no common words. To address this challenge, we employ semantic matching using sentence transformers (Reimers and Gurevych, 2019), which capture the underlying meaning of terms rather than just their textual similarity. This technique allows us to overcome vocabulary differences between our source texts and the Lightcast skills taxonomy.^{¶¶} For each Lightcast skill, we compute the average of the semantic proximity score between that skill and each low-carbon keyword. We classify skills that achieve an average proximity scores in the top percentile as low-carbon. This yields a further 35 low-carbon skills, such as “Clean Energy” and “Emission Reduction Projects”.

Step 3: Coverage extension through semantic clustering

We recognize that most Lightcast skills are not semantically unique. For example, “Solar Equipment”, “Solar Panels”, “Solar Energy Systems” and “Solar Photovoltaic Panels” are distinct in the Lightcast taxonomy but semantically similar to each other. The three signals of Step 2 identify “Solar Equipment” and “Solar Panels”, but not the other two solar-related skills. To address such potential gaps, we apply agglomerative hierarchical clustering to regroup the 16,000+ Lightcast skills into 6,668 semantically consistent clusters.^{***} If one skill in a cluster is identified as low-carbon, all skills in that cluster are classified as low-carbon. This iteration adds 98 more low-carbon skills, including “Solar Energy Systems” and “Solar Photovoltaic Panels” from the above example, along such skills as “Climate Policy”, “Carbon Accounting” and “Weatherization Installation” among others.

Step 4: Exclusion for decarbonization focus and of false positives

To sharpen the focus on decarbonization and avoid false positives, we exclude job ads that simultaneously contain both high- and low-carbon skills, and apply a targeted exclusion list with three parts: i) green but non-climate skills (*e.g.* water treatment or environmental remediation) are excluded because O*NET green tasks can conflate environmental and low-carbon content; ii) generic energy-related skills that are not specific to decarbonization (*e.g.* nuclear); iii) fossil-fuel related skills which can be semantically

^{¶¶}For example, patents typically use specialist, technical vocabulary that differs from the more generalist language found in job advertisements.

^{***}We apply agglomerative hierarchical clustering on the high-dimensional semantic vector representation (*i.e.*, sentence embeddings) of skills that we obtained to perform semantic matching. This allows us to automatically identify skills that are conceptually related (*e.g.*, “Python programming”, “R programming”, and “statistical software” would form a cluster) without requiring manual classification. The resulting 6,668 clusters provide a more tractable unit of analysis while reducing noise from near-duplicate skills.

close to decarbonization skills and therefore yield false positives. These are implemented as a combination of a limited number of excluded Lightcast skill categories and excluded keywords, as documented in Table B.2. These non-climate green and gray job ads are reintroduced in sensitivity tests (Table B.4 lists skills that are reintroduced for this sensitivity analysis). Finally, a set of brand-name false positives that include low-carbon related terms (such as *e.g.* software systems “Solaris”, “Sunguard” or “Greenplum”) listed in Table B.3 are excluded.

Through this four-step algorithm, we identify 389 low-carbon skills, which we call “low-carbon job identifiers” (listed in Tables B.5-B.7). A job posting is considered low-carbon if it contains at least one of these identifiers. Out of the 200 million job ads in the Lightcast data, approximately 1.8 million are identified as low-carbon. Table B.8 lists the most common low-carbon identifiers, which relate to energy efficiency, conservation, and renewable energy. Examples of typical low-carbon job ads are provided in Table B.9.

We ensure that our results are robust to the use of alternative thresholds at each step of the algorithm, and that our main findings remain unchanged when we relax our exclusion list to include non-climate green skills and nuclear energy in Appendix B.2.

2.3 Identifying high-carbon ads

To explore the impact of the low carbon transition on workers, we also identify jobs at risk of displacement. In contrast to low-carbon jobs, high-carbon jobs, being associated with incumbent fossil-fuel technologies, are better captured by extant sector and occupational classifications. Similar to Vona et al. (2018) and to subsequent works (Bluedorn et al., 2023; Popp et al., 2021; Zhang et al., 2025), we use the concentration of an occupations in polluting industries to identify brown jobs. Specifically, we follow (Popp et al., 2021) and define high-carbon jobs as those that are in one of the two major occupational group containing high-carbon roles (i.e. engineering and construction & extraction) and are engaged in fossil-fuel related tasks (complete list in Appendix Table B.10).^{†††} This definition focuses on jobs that will unavoidably disappear with decarbonization. Hence, we exclude jobs in carbon-intensive manufacturing industries, which may become greener in the future. This approach identifies around 200,000 vacancy postings^{†††} (approximately 0.3% when weighted by BLS employment).

2.4 Cross-validation with the task-based approach

To assess the validity of our classification, we benchmark our skill-based identification of low-carbon jobs against the widely used task-based classification of green jobs (e.g. Vona et al., 2019; IMF, 2022; Elliott et al., 2024), in which the “greenness” of an occupation is defined by the share of green tasks relative to total tasks, based on O*NET data.

^{†††}The share of high-carbon job vacancies by occupation is shown in Table C.1.

^{†††}A small subset of these high-carbon ads (less than 10,000 ads) are also flagged as low-carbon. We exclude these jointly high- and low-carbon ads from the rest of our analysis.

To enable comparison, we compute, for each occupation, the share of job ads classified as low-carbon in the Lightcast dataset and benchmark it against the corresponding task-based measure at the same occupational level. Because O*NET green tasks covers a broader spectrum of green beyond those relevant to low-carbon, we construct a refined subset of low-carbon-specific tasks from O*NET (see Appendix J.1 for details). As shown in Appendix J.2, at the SOC 2-digit level, the correlation between our ad-based approach and the task based approach is strong, whether with the original O*NET green tasks (first panel), or the selection of low-carbon O*NET green tasks (second panel). We additionally cross-validate our results on low-carbon employment shares through comparison with the task-based approach in section 3.

2.5 Key occupations for the energy transition

To examine the differences between low-carbon and non low-carbon jobs within occupations, we focus on six occupations with a high density of low-carbon job ads. These are chosen based on both low-carbon job shares and absolute numbers, as explained in Appendix C. They are four high-skilled 3-digit SOC occupations: Business Specialists (13-2); Engineers (17-2); Engineering & Mapping Technicians (17-3); and Physical Scientists (19-2), as well as two low-skilled 2-digit occupations: Construction & Extraction (47); and Installation & Maintenance (49). The 2-digit level is chosen for low-skilled occupations because workers' mobility across-occupation is possible with some investments in training, whereas high-skilled workers typically require substantial formal education to transition between 3-digit occupations (e.g. biology to physics). These key occupations align closely to those identified as most green-task intensive using O*NET data (Vona et al., 2019).

In the following sections, we focus on the 6 key occupations, and leverage this dataset to explore the barriers to reallocation to low-carbon jobs, specifically by assessing the skill, wage, and spatial gaps.

3 Employment share of low-carbon jobs

In the absence of a universal and operational definition of low-carbon jobs, it is unsurprising that estimates of green employment vary widely in the literature depending on the level of analysis (e.g., sector or occupation), the methodology chosen and the granularity of the data (Vona, 2021; Apostel and Barslund, 2024). Within occupation-based estimates, the upper end results from using the binary approach whereby all employment in an occupation involving a green tasks is considered green (Bowen et al., 2018; Valero et al., 2021; OECD, 2024), while the over-estimation can be corrected using the continuous approach that re-weights employment shares by the share of green tasks over total tasks as proposed by Vona et al. (2019), resulting in more moderate figures (Vona, 2021).

Our estimates suggest that even the most conservative estimates may have overstated the scale of green job creation. As shown in Figure 1, the employment-weighted share of low-

carbon jobs averaged just 0.9% of the U.S. workforce between 2010 and 2019, equivalent to approximately 1.3 million workers.^{§§§} This lower figure partly reflects our focus on low-carbon activities specifically, rather than the broader set of environmental activities (e.g. water, waste, remediation, and gray energy jobs such as those linked to nuclear) typically included in earlier studies - many of which are labour-intensive.

We argue that our methodology offers a more accurate measure of the true scale of low-carbon employment, as it allows for job-level identification of relevant skills within occupations, rather than assuming all roles in a firm or sector are uniformly green. Interestingly, despite relatively modest progress on decarbonization in the U.S. during the sample period - total greenhouse gas emissions declined by only 6.2% ([U.S. Energy Information Administration, 2021](#)), and the shale gas production expanded significantly - low-carbon jobs still accounted for a larger share of employment than jobs in high-carbon extraction sectors averaging 0.27% between 2010 and 2019 (see [Figure E.1b](#)).

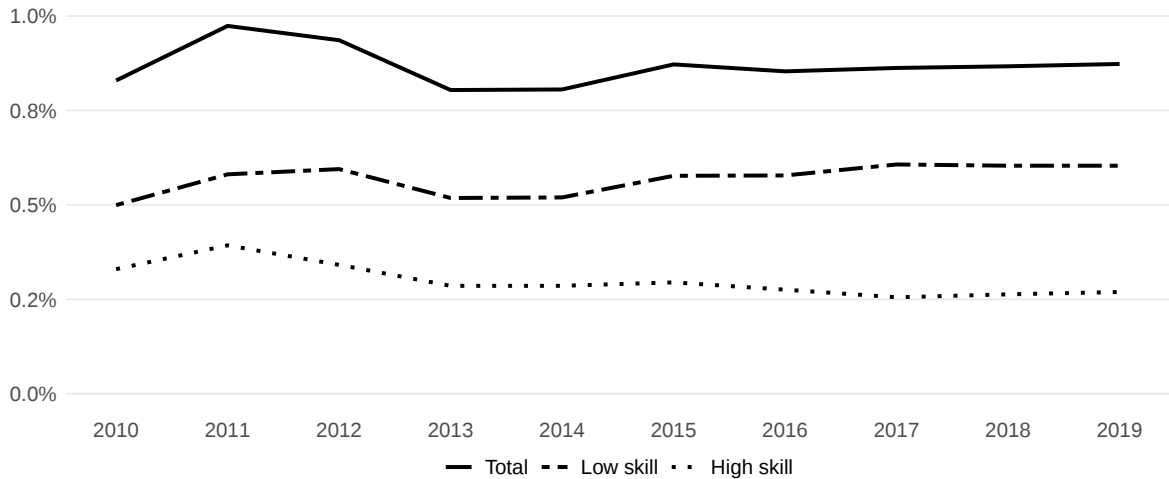


Figure 1: Evolution of low-carbon vacancy shares in the U.S. (2010-2019)

Notes: Plotted shares of low-carbon ads are first calculated at the 6-digit SOC occupation level as the ratio between the number of low-carbon ads and the total ads within a 6-digit occupation, then averaged for each reported SOC grouping weighing by 6-digit employment obtained from the BLS. Includes all occupations. *Source:* Lightcast and BLS.

Over the past decade, the share of low-carbon vacancies in total job postings remained relatively stable ([Figure 1](#)). This contrasts with the steady decline observed in high-carbon jobs ([Figure E.1b](#)), and with the growth seen in renewable power-related jobs ([Popp et al., 2021](#); [Curtis and Marinescu, 2023](#)). More specifically, our data shows a modest increase in the share of low-carbon job postings from 0.83% in 2010 to 0.97% in 2012, coinciding with the job creation effects of the American Recovery and Reinvestment Act (ARRA) ([Aldy, 2013](#); [Popp et al., 2021](#)). This was followed by a period of decline and stabilization

^{§§§} As indicated in the Figure notes, here we include all occupations and not only the 6 key occupations identified in [Section 2.5](#) in order to gain a general understanding of the share of low-carbon jobs in the U.S. economy.

around 0.80%, before rising again from 2015 onwards.^{¶¶¶}

A particularly noteworthy finding is that low-carbon jobs are more concentrated in low-skilled occupations, and this share has increased over time. Our data reveals divergent trends: the share of low-carbon jobs in high-skilled occupations declined from 0.39% in 2010 to 0.26% in 2019, while for low-skilled occupations, the share increased from 0.50% to 0.61% over the same period (Figure 1) and Table E.1). The evolution of low-carbon job shares is also highly heterogeneous across the six most relevant occupations as shown in Appendix Figure E.1a. Notably, the share of low-carbon vacancies declined for Business Specialists (from 3.0% to 1.6%) and Engineers (from 5.5% to 3.9%) while it increased in Construction and Installation.

This finding - that low-carbon vacancies are more concentrated and growing only in low-skilled occupations- is an encouraging signal for the prospects of a just transition, while earlier studies suggest that the green transition is likely to be skill-biased, favoring high-skilled workers at the expense of those with lower qualifications (Marin and Vona, 2019). It is also somewhat surprising given that, over the last five decades, technological change has been associated with a shift in demand towards high-skilled workers and increased income inequality (Katz and Murphy, 1992; Acemoglu, 2002; Acemoglu and Autor, 2011; Autor et al., 2016). At the same time, this pattern echoes prior evidence on the job creation effects of ARRA’s green investments that primarily targeted manual and low-skilled occupations (Popp et al., 2021). Thus, expansion of low-carbon employment opportunities in low-skilled segments of the labor market may help to partially offset to the longer-term trend of deteriorating labor market conditions for low-skilled workers.

To cross-validate our methodology, we reproduce low-carbon employment shares based on the task-based approach and compare the results with our own estimates (see Appendix J.3). While our measure suggests that low-carbon jobs accounts for 0.9% of total employment, the task-based approach yields a higher share of 3.2% when applying the broader ONET green definition, consistent with prior studies (Vona et al., 2019). When using only the low-carbon subset of O*NET tasks, the estimated share is lower at 1.5%, and thus much closer to our own estimate. The fact that we obtain results within a comparable range, particularly when focusing on low-carbon-specific tasks in O*NET, reinforces confidence in the validity of our classification. Given the finer resolution of our job-level, skill-based approach, we consider it likely to offer a more precise approximation of the true share of low-carbon jobs in the economy.

Sensitivity checks (Appendix Table I.3) confirm that reasonable changes in cut-offs do not strongly affect the low-carbon shares. For instance, relaxing the frequency threshold

^{¶¶¶}After adjusting for multiple hypothesis testing using the Bonferroni correction, all trends are statistically significant.

by 10% (column b) and expanding low-carbon skills to include gray skills (column h) increases the overall number and share of low-carbon jobs by around 1.2% and 1.1% respectively.

4 Skill gaps

The expectation that significant workforce reallocation is needed under ambitious decarbonization scenarios (Hafstead and Williams III, 2018; Castellanos and Heutel, 2024) raises concerns over skill gaps, which have been identified as a primary obstacle to the reallocation of workers across occupations (Poletaev and Robinson, 2008; Kambourov and Manovski, 2009; Gathmann and Schönberg, 2010). This section shows that low-carbon jobs systematically demand more skills, and more diverse set of skills compared to their non-low-carbon counterparts, even within the same occupation or firm. In other words, even if the low-carbon transition is not biased in favor of high-skilled workers, it requires substantial retraining within existing occupations. We also show that reskilling requirements are highly occupation-specific, pointing to the need for targeted retraining strategies.

4.1 Within and between occupational green skill gaps

To assess the differences in skill requirements of low-carbon and similar non low-carbon jobs, we build a measure of the green skill gap based on the frequency of specific skills being observed in low-carbon job postings relative to generic ads. This intuitive frequency-based measure has been previously used to deal with data that do not provide information on skill importance, such as OJV data (Deming and Kahn, 2018; Deming and Noray, 2020) or German task data (Spitz-Oener, 2006; Gathmann and Schönberg, 2010). Importantly, the specific green skill used to identify the job as low-carbon is always excluded from the comparison.

Denoting the share of job ads that mention skill s within 6-digit occupation k and job type i - either low-carbon ($i = g$) or generic ads $i = ng$ - as $f_{sk}^i = \frac{n_{sk}^i}{n_k^i}$, we define the aggregate low-carbon skill gap for skill group s as:

$$f_s^g - f_s^{ng} = \sum_k \omega_k^g \omega_k \times (f_{sk}^g - f_{sk}^{ng}), \quad (1)$$

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 low-carbon jobs in total jobs for occupation k and ω_k is the employment share of occupation k , accounting for the size of the occupation. This measure reflects both within-occupation and between-occupation differences in skill demand and to further disentangle these effects, we decompose the skill gap as follows:

For 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 6-digits.

$$f_s^g - f_s^{ng} = \sum_k \omega_k^g \omega_k \times [(f_{sk}^g - f_{sk}^{ng}) + (f_{sk}^{ng} - f_s^{ng})]. \quad (2)$$

The second element in the square bracket is the between-occupation component of the skill gap - that is, the extent to which the share of low-carbon jobs (ω_k^g) correlates with the difference in skill use across occupational groups. This component is the focus of prior research using occupation-level data. The first element instead captures the within-occupation skill gap - that is, the difference in skill intensity between low-carbon and generic jobs within the same occupational group. This dimension is unobservable in occupation-level datasets and can be estimated for the first time in our study thanks to the high granularity of the OJV data. This decomposition allows us to quantify the extent to which earlier research may have underestimated the true scale of skill gaps.

To make the Lightcast data’s skill multidimensionality more tractable, we then follow the approach of [Deming and Kahn \(2018\)](#) and group skills into five broad categories — cognitive, social, IT, managerial, and technical. This grouping aligns with prior research highlighting the importance of cognitive, social, and managerial skills in tasks less prone to automation ([Autor et al., 2003](#); [Deming, 2017](#)), and the specific relevance of technical skills to green technologies in the workplace ([Vona et al., 2018](#)).

Table 1 reports the results of the decomposition for each five broad skill category, using four different weighting schemes resulting from the combination of different choice of ω_k^g and ω_k in each column. Four key results emerge. First, skill gaps are consistently positive across all categories, indicating that low-carbon jobs require more skills than comparable roles. Second, the within-occupation component significantly contributes to the overall gap, suggesting that previous occupation-level analyses underestimated the true extent of the reskilling challenge. Third, the within-component is especially larger for managerial, social, and technical skills where it accounts for up to one-third of the overall gap. This confirms the technical and managerial skill bias of green activities previously found ([Vona et al., 2018](#); [Marin and Vona, 2019](#)). Finally, a novel finding here is that green jobs also require social skills more than generic jobs.

The average green skill gap may mask differences in the scale of these gaps across occupations, and we explore this heterogeneity, by comparing the prevalence of skills in the five

For example, ([Vona et al., 2018](#)) estimate the skill gap using the covariance between the occupational green task intensity (ω_k^g) and the across-occupation skill gaps ($f_{sk} - f_s$). In O*NET-based studies, f_{sk} is observed, but f_s^{ng} is not. Because the share of green jobs in each occupation is small, f_s^{ng} is highly correlated with f_s .

More specifically, skills are classified into five groups using a set of keywords provided by ([Deming and Kahn, 2018](#)) except for IT skills that uses the Lightcast IT skill family (see Table F.1 for a complete list) and technical skills that use ([Vona et al., 2018](#)) (see Appendix Table F.1).

The former is either the green task intensity from O*NET or the share of low-carbon task from Lightcast data. The latter is either the 6-digit occupational employment share from BLS or the number of Lightcast job ads.

broad skill categories across low-carbon (f_{sk}^g), high-carbon (f_{sk}^b) and generic job postings (f_{sk}^{ng}). Figure F.1 in the Appendix shows that, consistently across occupations and broad-skill types, a higher share of low-carbon jobs demand these skills, both at the extensive margin (one skill mentioned) and the intensive margin (two or more skills mentioned). However, the size and significance of the gaps indeed, differ by occupation (see also the corresponding Table F.2 in Appendix for details). Larger skills gaps are observed for Engineering technicians and Installation & maintenance workers, especially for managerial, technical and social skills, indicating potential challenges in filling low-carbon vacancies in these occupations. Technical skills drive much of the gap for Business Specialists, while management and IT skills drive the gaps in Construction. When examining the shift from high- to low-carbon jobs, we find that high-carbon ads also require more skills compared to generic jobs. This suggests a narrower skill gap between low- and high-carbon ads, as previously noted (Vona et al., 2018; Popp et al., 2021; Lim et al., 2023). However, it is noteworthy that for engineers, low-carbon vacancies demand more skills than high-carbon ones (Appendix Table F.2).

Table 1: Skill gaps between low carbon and non-low carbon jobs, within and between occupations

	O*NET greenness $\times$ Employment share	Low-carbon share $\times$ Employment share	O*NET greenness $\times$ Job ads share	Low-carbon share $\times$ Job ads share
Cognitive	21.03%	17.87%	25.88%	22.92%
Within-occupation	2.59%	2.81%	2.87%	2.79%
Cross-occupation	18.45%	15.06%	23.02%	20.13%
IT	26.70%	22.19%	33.53%	29.61%
Within-occupation	2.47%	2.58%	2.82%	3.13%
Cross-occupation	24.23%	19.61%	30.71%	26.48%
Management	35.34%	29.35%	39.22%	36.39%
Within-occupation	8.29%	8.20%	10.51%	10.45%
Cross-occupation	27.05%	21.15%	28.72%	25.94%
Social	38.96%	33.84%	44.58%	41.78%
Within-occupation	7.44%	7.41%	9.44%	9.23%
Cross-occupation	31.53%	26.44%	35.14%	32.55%
Technical	32.73%	26.78%	36.86%	34.13%
Within-occupation	8.68%	9.29%	9.18%	10.52%
Cross-occupation	24.05%	17.49%	27.68%	23.61%

We exploit the spatial variation across Commuting Zones (CZ) in the share of low-carbon ads in specific occupations to compute confidence intervals (see Table F.3 for details). Commuting Zones, as defined by the U.S. Department of Agriculture (USDA) Economic Research Service (ERS) are geographic units intended to more closely reflect the local economy where people live and work.

Notes: Here we stack together the 6 key occupations identified in Section 2.5, weighting them by BLS employment. This table shows the within- and between-occupation skill gaps for five major skill categories as defined by Equation 2. Skills are categorized using a set of key words as detailed in main text. These are calculated using 4 different combinations of weights ω_k^g and ω_k (in columns). Skill gaps are reported in percentage points, multiplying the difference in the shares by 100 for readability. *Source:* Lightcast and BLS.

4.2 Skill complexity

Our results so far suggest that low-carbon jobs require a broader and more diverse range of skills than comparable non-low-carbon roles. This pattern is consistent with the idea that low-carbon jobs involve more complex tasks, as previous research has shown that job complexity is strongly linked to the number and diversity of the skills required (Deming, 2017; Alabdulkareem et al., 2018; Deming, 2023; Stephany and Teutloff, 2024). This pattern is evident in OJV data where ads of high-skilled jobs require more skills than ads of low-skilled jobs.

Table 2: Skill vector length of generic, low- and high-carbon jobs by occupation

	Generic	Low carbon	High carbon
13-1 - Business Operations Specialists	11.5	14.8	
17-2 - Engineers	11.9	16.2	10.6
17-3 - Engineering and Mapping Technicians	9.5	14.5	
19-2 - Physical Scientists	10.9	15.7	
47 - Construction and Extraction	6.3	10.0	7.9
49 - Installation, Maintenance, and Repair	8.4	13.4	
All occupations	9.3	14.1	9.2

Notes: This table shows the average skill vector length of generic, low-carbon and high-carbon job ads in our sample, by 3-digit (for high skilled) and 2-digit (for low-skilled) SOC groups, for the years 2010 to 2019. *Source:* Lightcast.

Concerning low-carbon ads, Table 2 shows that they require more skills per ads, and thus are more complex than generic ads, within the same occupation and after excluding the specific green skills used to identify the job as low-carbon. Two possible explanations can account for this pattern. First, firms may write more detailed postings to attract applicants regardless of job complexity. However, this result holds even after including firm fixed effects to control for unobservable heterogeneity, for example in job advertising strategies (Table 3 and Appendix Table 2). Second, green jobs may represent new job types, requiring employers to specify more skills to ensure a suitable match. However, the difference in skill vector length between low-carbon and generic jobs remains stable

On average in 2019, more skills are contained in high-skilled job ads (e.g. 17 - Architects & Engineers and 19 - Scientists) with a median of 10 skills per ad, than in low-skilled job ads (e.g. 47 - Construction & Extraction and 49 - Installation, Maintenance & Repair) with a median of 7 skills per ad.

This result is robust to winsorizing the skill length at 30 skills per ad (see Appendix Table F.4). Appendix Table I.4 also shows that our finding that low-carbon jobs have higher skill requirements is robust to the design choices made in the low-carbon skill selection algorithm, specifically the cut-offs used, and the inclusion of gray skill clusters in low-carbon skills.

through our sample period, rather than decreasing over time (see Appendix Figure F.2), indicating that the novelty of low-carbon roles is not the driver here.

Table 3: Within-firm differences in skill vector length between low carbon and generic ads

	13-1 - Business Operations Specialists	17-2 - Engineers	17-3 - Engineering and Mapping Technicians
Low carbon	1.561*** (0.228)	2.623*** (0.157)	2.953*** (0.227)
Mean length	12.45	13.02	10.65
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
R^2	0.3	0.27	0.4
Observations	6,549,642	2,957,995	1,397,391

	19-2 - Physical Scientists	47 - Construction and Extraction	49 - Installation, Maintenance, and Repair
Low carbon	2.379*** (0.230)	2.693*** (0.240)	2.618*** (0.424)
Mean length	11.95	7.7	9.26
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
R^2	0.41	0.52	0.47
Observations	284,835	1,235,908	5,017,358

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the skill vector length, which is regressed on a binary variable indicating whether a job ad is low carbon or not, and on firm fixed effects. *Source:* Lightcast. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Taken together, we find strong evidence that low-carbon jobs are systematically more skill-intensive requiring more complex skill profiles than comparable roles. This result motivates our subsequent analysis of whether these higher skill demands are also reflected in wage outcomes, as explored in Section 5.

4.3 Reskilling paths by occupation

Our findings that low-carbon jobs require a richer skill portfolio than similar non-low carbon jobs suggests that substantial re-skilling efforts will be required to enable the expected large scale mobilization of a greener workforce in the coming decades. To understand whether low-carbon jobs require workers to deepen existing competencies or to diversify beyond their occupational core, we introduce a new reskilling indicator measuring the direction of skill reorientation required by new and emerging jobs, such as low-carbon ones. This indicator is based on the correlation between two Balassa indices of skill prevalence,

New emerging jobs are often a main channel through which new skills enter the labor market (Lin, 2011; Autor et al., 2022) hence represent evolving roles in the labor market.

which has been used in previous research on skill differences across occupations (Alabdulkareem et al., 2018). The first index assesses the importance of a skill in low-carbon jobs with respect to non-low-carbon job within an occupation, while the second assesses the importance of the same skill across occupations as in Alabdulkareem et al. (2018), thus identifying core occupational skills (see Appendix F.1 for details). A positive correlation suggests that reskilling builds on existing skill set (specialization), while a negative correlation implies the need to acquire skills beyond the core (diversification).

Results reveal marked heterogeneity in reskilling path across occupations (Figure 2). STEM occupations, such as Engineers (0.07) and Scientists (0.13), exhibit positive and statistically significant correlations, suggesting that green transitions within these occupations involve deepening existing expertise as also shown by previous research (Vona et al., 2018; Popp et al., 2024). This is expected given that climate science and environmental engineering require the combination of multiple scientific domains. High-carbon engineering roles also show a path of specialization, again suggesting the relative ease of moving from high- to low-carbon engineering roles. Conversely, Business Specialists exhibit a pronounced negative correlation (-0.15), suggesting a diversification path beyond their core skill sets, perhaps in acquiring more technical or engineering-related skills. Engineering Technicians show a modest diversification pattern, although the correlation is sensitive to the specific skill subsets used.

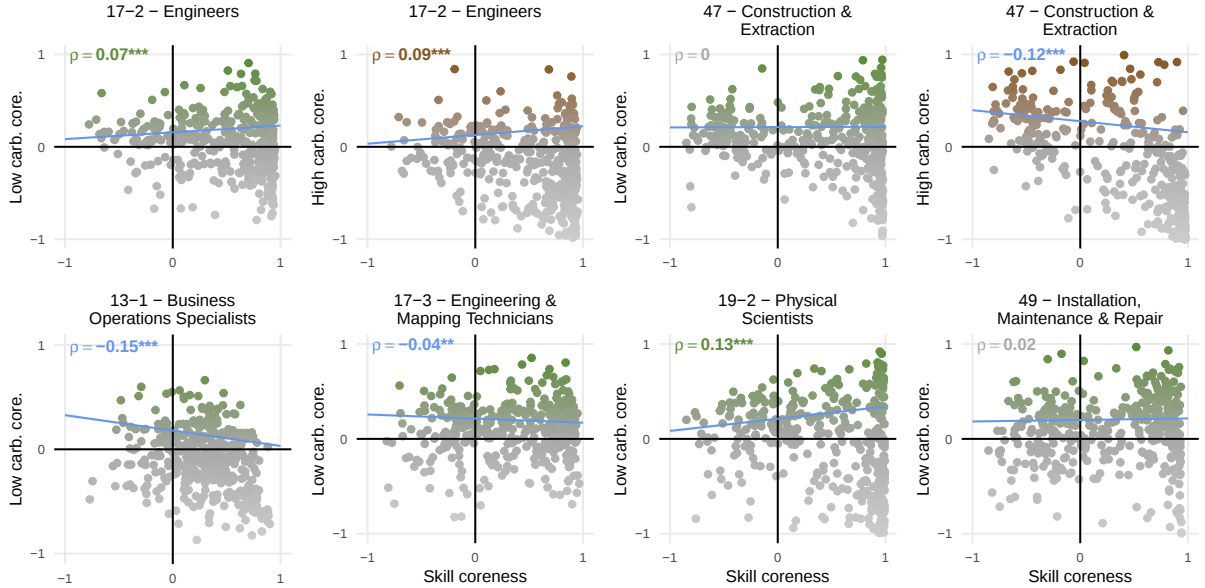


Figure 2: Specialization vs diversification by occupation

However, the positive correlation disappears for Scientists when highly specific skills ($C_{sk}^g > 0.9$) are excluded (see Appendix Figure F.3) or when we consider a subset of skill items belonging to the five key categories (see Appendix Figure F.4).

This result is robust to the different choices of the skills included as highlighted in Appendix Figures F.3 and F.4.

Notes: For each occupation, we plot the 400 most frequent skills mentioned in job postings, with each dot representing one skill. For Engineers (17-2) and Construction & Extraction, we separately plot this for low-carbon job ads (green colour) and high-carbon job ads (brown colour). A positive correlation (ρ) between C_{sk}^i (y axis) and G_{sk}^i (x axis) indicates *specialization* while a negative correlation indicates *diversification*.

For lower-skilled occupations, we do not observe clear specialization or diversification patterns, despite the presence of notable skill gaps (Figure F.1). This suggests that re-skilling for these roles may be highly context- and technology-specific, requiring context-specific solutions.

Overall, accounting for the within occupation variation reveals larger and more complex skills gaps than previously documented, with reskilling paths varying considerably by occupation. Whether these gaps are reflected in wage differentials is the focus of the next section.

5 Wage gaps

This section explores the attractiveness of low-carbon jobs by examining the wage offers posted in job advertisements. Prior studies generally find a positive wage premium for green jobs (Antoni et al., 2015; Muro et al., 2019a; Bluedorn et al., 2023; Curtis and Marinescu, 2023; Kuai et al., 2025; Whittard et al., 2025). We extend this literature by estimating wage premia for low-carbon jobs within narrowly defined occupations and firms, and find that these are positive but modest, and have declined over time. Consistent with evidence on skill gaps, we find that green wage premiums are higher for jobs that require a more complex skill set.

5.1 Empirical setting

Online job vacancy data allow us to observe the wage offers posted in job ads. These wage offers reflect hiring difficulties and demand-side labor market dynamism in particular sectors, but may differ from the equilibrium wages, which also accounts for supply-side factors such as the availability of candidates with the required competences. Previous research circumvents this potential problem by combining BLS wage data with skill data aggregated from job ads at the occupational level (Deming and Kahn, 2018; Atalay et al., 2020; Azar et al., 2020). However, such approach would only allow estimating an average low-carbon wage premium across-occupations (e.g. Vona et al., 2019; Bluedorn et al., 2023). Reassuringly, Lightcast wage offers are highly correlated with BLS wage data (Azar et al., 2020). This motivates our use of online job ads to compare wage offers between low-carbon jobs and comparable generic jobs within the same occupation. Our data also allows controlling for firm heterogeneity and other structural factors which is important given that green jobs still constitute a small share of employment within most occupations.

For example, 4% in the U.S. 2006-2014 (Vona et al., 2019), 7% in 2005–19 across 31 countries (Bluedorn et al., 2023), and between 4% to 10% in the UK in 2011-2018 (Whittard et al., 2025).

Moreover, this study provides similar results on the estimated association of labor market concentration and wages in local U.S. labor markets.

We use Mincerian wage regressions (Mincer, 1974) to estimate returns to low-carbon jobs, controlling for occupational fixed effects and other covariates for six occupations with a higher prevalence of low-carbon ads:

$$\log(w_{iot}) = \beta_{lc}\mathbb{1}\{i \in lc\} + \mathbf{X}_{it}\mu + \gamma_o + \alpha_t + \varepsilon_{it}, \quad (3)$$

where i indexes the job ad, o occupation, and t time. The variable of interest is $\mathbb{1}\{i \in lc\}$ and associated coefficient β_{lc} captures the average return to low-carbon jobs compared to generic jobs in the same occupation, as we include occupational fixed effects γ_o (3-digit SOC), to capture exposure to other structural factors, such trade or automation. Equation 3 is estimated separately for three sub-periods (2010-12 and 2017-19), including year fixed effects α_t to control for common shocks within each sub-period. Importantly, wage information is available only for around 21% of job ads. Estimations are weighted by the BLS employment at 6-digit SOC level to address sample representativeness concerns (see Table G.1), Standard errors are clustered at the commuting zone level because postings within the same local labor market are likely to share unobserved shocks (e.g., local demand, cost of living, state policies), inducing correlated residuals across ads within CZs over time.

We exploit the rich information contained in online job ads to construct a vector of controls $\mathbf{X}_{it}$, that rules out major sources of spurious correlation. Because such additional information are present only for a subset of job ads, we present two specifications. In a basic specification that maximizes the number of observations, we add only 3-digit occupation fixed effect, dummies indicating the commuting zones where the ad is posted, and dummy variables for skill vector length bins. In our favorite specification, we include firm fixed effects, to account for wage differences driven by firms (Abowd et al., 1999; Song et al., 2019) due for example to differences in rents and productivity.

Attributing a causal interpretation to estimated returns to low-carbon ads is not possible for several reasons e.g. ads posting wage information may be self-selected, both within and across occupations (e.g. Banfi and Villena-Roldan, 2019) and an exogenous source of variation is absent here. Nonetheless, the most demanding specification rules out the possibility that major sources of endogeneity, such as pre-existing firm-specific rents and productivity levels, or occupation-level measures of exposure to other structural factors are contaminating the estimates of low-carbon wage premium.

We are stacking 3 years to look at the dynamics and smoothen yearly fluctuations. This also allows us to increase sample size.

In particular, five dummies corresponding to skill vector lengths of 1-4, 5-8, 9-12, 13-16, 17+ are included.

5.2 Low-carbon wage premium

Table 4 presents the main result on the wage premium associated with low-carbon jobs relative to similar jobs. Overall, we find that low-carbon job ads offer higher wages, compensating for their higher skill requirement of low-carbon roles. Focusing on the basic specification (columns 1, 3 and 5), returns are more pronounced in the earlier period (2010-2012) compared to the later period (2017-2019), consistent with shifts in U.S. climate policy after the green ARRA stimulus. Relative to salaries in similar jobs, low-carbon jobs command a 7.9% premium in the first period of the ARRA green push (column 1) and 4.5% in the second period characterized by a reduced ambition in U.S. green policies (column 3).

Table 4: Relationship between low-carbon job and wage offer

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.079*** (0.010)	0.052*** (0.010)	0.045*** (0.005)	0.030*** (0.004)	0.065*** (0.005)	0.037*** (0.004)
Mean wage (\$2019)	66,352	70,019	58,823	57,410	60,461	59,554
Observations	759,507	273,544	2,418,122	1,600,343	4,748,666	2,578,408
R^2	0.27	0.74	0.23	0.69	0.24	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: We stack the data for the 6 key occupations identified in section 2.5, weighting them by BLS employment. Within each column, we present coefficient estimates and standard errors corresponding to estimates of equation 3. Skill vector length fixed effects are grouped as follows: 1-4, 5-8, 9-12, 13-16 and 17+ skills per job ad. Standard errors are clustered at the commuting zone level.

Importantly, the low-carbon wage premium are substantially reduced when we include firm fixed effects (columns 2, 4 and 6). Quantitatively, the size of the premium is reduced by more than one-third compared to the basic specification: 5.2% in the first period, 3.0% in the second and to 3.7% overall. Because firm fixed effects capture rents and productivity differentials unrelated to low-carbon tasks, this specification is the most accurate and reliable to quantify the size of the low-carbon wage premium. By failing to account for firm wage differentials, previous research tends to overstate the size of the green wage premium (Vona et al., 2019; Bluedorn et al., 2023; Curtis and Marinescu, 2023; Kuai et al., 2025; Whittard et al., 2025). This finding also implies that workers may not be fully compensated for their better skillsets in low-carbon roles.

The key role of firm fixed effects in accounting for the low-carbon wage premium suggests some positive sorting of low-carbon work into firms that pay higher wages. That is, higher

paying firms also exhibit a higher share of low-carbon jobs. This insight is supported by correlating the firm share of low-carbon jobs and the firm fixed effects (see Appendix Table G.2 and Figure G.2).

Next, we estimate the low-carbon wage premium separately for the key six occupations defined in Section 2.5. Our estimates in Table G.8 and Figure G.1 suggest that the low-carbon wage premium and its decline varies substantially by occupation. Most occupations display a positive premium in the early period, especially Technicians (14%), Business Specialists (11.2%), and Installers (8.5%), but this premium declines in the later period to 6.4%, 10% and 5.6% respectively. The decline is particularly pronounced in high-skilled STEM occupations (i.e., Engineers and Scientists), where the low-carbon wage premium even becomes negative in the later period. Besides on the phasing out of the ambitious green subsidies program under the ARRA, the narrowing of the low-carbon wage premium can reflect labour market dynamics. On the one hand, Figure 1 showed that the demand of low-carbon roles slowed down especially for high-skilled workers, possibly reflecting a productivity differentials between STEM employed in low-carbon vs. non-low-carbon jobs. On the other hand, the adjustment in the supply of low-carbon training and educational programs may have contributed to absorb the skill-related part of the premium, especially in low- and medium-skilled occupations. A detailed investigation of these channels is beyond the scope this paper and is left for future research.

We also estimate wage premia for high-carbon jobs using the same specification of equation 3. Table G.9 in the Appendix shows that the high-carbon wage premium is significantly higher than the low-carbon one in the basic specification. The premium is strikingly high and stable (around 17%) especially in Construction and Extraction jobs, while it declined substantially in Engineering jobs (from 26% in 2010-2012 to 6.1% in 2017-2019), possibly reflecting the small number of high-carbon engineering ads in our sample. Notice that the premium for low-carbon role in construction is zero Remarkably, including firm fixed effects significantly reduces these premia and their statistical significance. This points to rent-sharing as the key driver of the high-carbon wage premium, also highlighting the traditional strength of unions in fossil-fuel sectors (Haywood et al., 2024; Muttitt and Kartha, 2020; Carley and Konisky, 2020).

The declining low-carbon wage premium alongside a relatively high wage premium for high-carbon jobs in similar occupations (i.e. construction and engineering) reinforces the concerns around the relative attractiveness of low-carbon jobs. This might draw skilled engineers and construction workers, in short supply, to high-carbon industries, diminishing the talent pool to tackle climate issues (Popp et al., 2024). In particular, the presence of large wage gaps in occupations like Engineering and Construction & Extraction where

In this case, firm fixed effects are retrieved from regressing the specification of equation 3 without the low-carbon dummy.

we expect transitions from brown to green, is consistent with previous findings that few workers have transitioned from high- to low- carbon jobs so far (Curtis et al., 2023).

5.3 Returns to skill complexity and skill types

Section 4.2 documented higher skill complexity of low-carbon jobs. To reinforce this, we estimate the differential returns to complexity in low-carbon ads by replacing the skill vector length dummies with the logarithm of the number of skills specified in the ad (proxy for skill complexity), interacted with the low-carbon dummy. We find significantly higher wage offers in low-carbon ads, only for ads posting more than 2.7 skills (based on specification (9) in Appendix Table G.10. See also Figure 3.). The low-carbon wage premium is zero below that threshold, corresponding to the 29th percentile. This result is consistent with the fact that low-carbon ads demand more skills, which is rewarded in the job market.

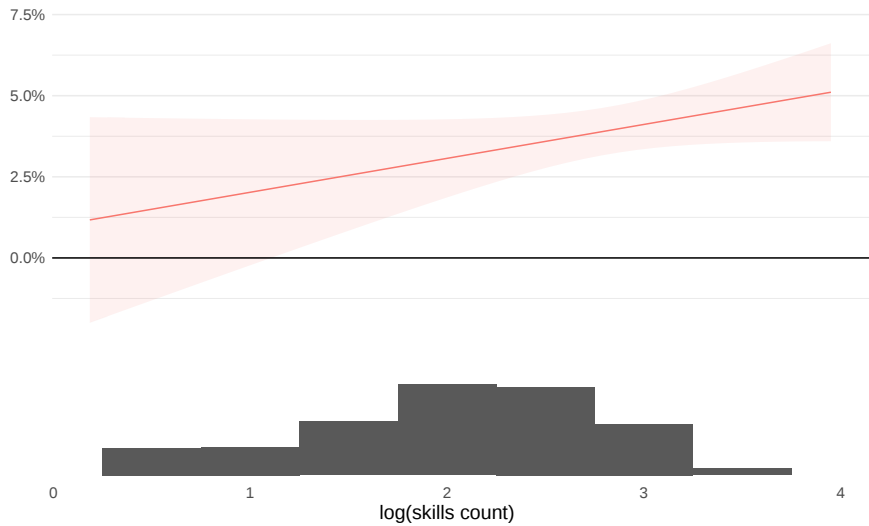


Figure 3: Marginal effect of job ad complexity on low-carbon wage gap

Notes: We stack the data for the 6 key occupations identified in section 2.5, weighting them by BLS employment. We estimate specification (9) of Table G.10 across our 6 occupations of interest over the period 2010-2019. The plotted line presents the marginal effect of the interaction between a job ad being low-carbon and the logarithm of its number of skills. The shaded area indicates the 95% confidence interval, with standard errors clustered at the CZ level.

Figure G.3 shows the coefficient capturing the returns to skill complexity for low-carbon ads by key occupation. Returns to skill complexity are generally higher in low-carbon ads across occupations, reflecting growing demand for diverse skills in green industries. The exceptions are Engineers and Construction workers, for whom returns to skill complexity are lower in low-carbon jobs. Our findings resonate with research showing that more diverse and complex skill sets are usually associated with higher earnings (Anderson, 2017; Deming, 2017; Neffke, 2019; Stephany and Teutloff, 2024). For instance, using online freelance project data, Stephany and Teutloff (2024) show that the value of a given skill increase with the number of other complementary skills required to perform a task, and this effect is stronger for new skills such as those related to AI. Because both AI and

low-carbon tasks are related to new technologies, the higher value of complex skill sets likely reflects still ill-defined skill requirements in new work, which reward workers with versatile skill portfolios.

Figure G.3 reports the coefficient capturing the returns to skill complexity for low-carbon ads by key occupation. Returns to skill complexity are generally higher in low-carbon ads across occupations, reflecting growing demand for diverse skills in green industries. The exceptions are engineers and construction workers, for whom returns to skill complexity are lower in low-carbon jobs. Our findings align with research showing that broader, more complex skill sets are typically associated with higher earnings (Anderson, 2017; Deming, 2017; Neffke, 2019; Stephany and Teutloff, 2024). For example, using online freelance project data, Stephany and Teutloff (2024) show that the value of a given skill increases with the number of complementary skills required to perform a task, and that this effect is stronger for new skills such as those related to AI. Because both AI and low-carbon tasks are tied to new technologies, the higher value of complex skill sets likely reflects still-ill-defined skill requirements in new work, which disproportionately reward workers with versatile skill portfolios.

Lastly, drawing insights from multidimensional skill models (Guvenen et al., 2020; Deming, 2023), we explore returns to specific sets of skills in low-carbon jobs by interacting the low-carbon ad dummy with measures of the importance of technical, cognitive (including IT skills), and social (including managerial) skills in regressions. Appendix Table G.11 demonstrates that while technical, social and cognitive skills are valuable across all occupations, returns to social skills are particularly pronounced in low-carbon jobs. In turn, technical and cognitive skills are less valuable in low-carbon jobs. The lack of additional returns to technical skills in low-carbon ads may be due to technical skills being inherent to the core skill set required for the key occupations studied here, resulting in fewer high-pay ads emphasizing them. Conversely, the high returns to social skills in low-carbon roles align with a broader trend highlighted by Deming (2017), where social skills command higher pay in emerging jobs such as those in low-carbon. However, these high returns to social skills may also indicate a firm’s emphasis on projecting a green corporate image through communication rather than substantial investments in green technologies (Chen, 2022). Future work could account for worker-job sorting and firm-level decarbonization strategies to further evidence the specific skills and green wage premium link.

We show that our results remain qualitatively similar under multiple robustness checks in Appendix G, including: winsorizing postings with extreme skills vector lengths (> 30) (Table G.3); using a consistent sample (Table G.4); excluding of 3-digit occupation fixed

We use the log of the number of technical, cognitive and social skills that are advertised in the post.

These patterns are confirmed when we use a binary measure of the presence of technical, cognitive and social skills in the ad (see Table G.12 in the Appendix).

effects (Table G.5); adding industry (NAICS 2-digit) and education requirement fixed effects (Table G.6); and estimating without BLS employment weights (Table G.7). We also estimate a fully flexible specification that interacts the low-carbon indicator with year fixed effects (Appendix Table G.13) as these are more general than the piecewise-constant time structure implied by stacking years into subperiods, because they allow arbitrary common shocks and non-parametric dynamics in the premium.

Results on wage premium are also robust to key design choices in the low-carbon skill selection algorithm including alternative cut-offs and the inclusion or exclusion of gray skill clusters, as shown in Appendix Table I.5 and Figure I.2.

6 Spatial gaps

One of the key challenges in delivering a “just transition” and enhancing the political acceptability of the green transition is to ensure that displaced manual workers in carbon-intensive industries or left-behind regions can find new jobs with similar pay and working conditions (Vona, 2019; Weber, 2020; Hanson, 2023). Addressing their prospects is important, also to neutralize job killing arguments used by fossil fuel lobbies to oppose climate action (Vona, 2019).

Evidence from deindustrialization shows that negative shocks are spatially concentrated and persistent, with multiplier effects that propagate through local demand linkages (Autor et al., 2016, 2021); accordingly, regions heavily reliant on carbon-intensive activities are likely to face larger and longer-lasting impacts (Hanson, 2023). Against this background, this section seeks to deepen understanding of the spatial distribution of high- and low-carbon jobs focusing on low-skilled jobs, to help better manage the negative effects of climate policies.

We compare the geography of emerging low-carbon opportunities with that of incumbent high-carbon employment. Specifically, we juxtapose low-carbon vacancies (flows) job ads), which proxy where new demand is arising in the short run (Deming and Kahn, 2018; Atalay et al., 2020), with high-carbon employment (stocks), which better capture the location of workers at risk in legacy, declining industries central to the U.S. just-transition debate (Weber, 2020; Popp et al., 2021; Autor et al., 2021; Hanson, 2023). This approach also aligns with recent evidence that location—rather than skill per se—poses a first-order barrier to reallocating fossil-fuel workers into clean energy, given limited co-location of opportunities despite substantial skill overlap (Lim et al., 2023).

Figure 4B maps the top 15% of areas with the highest shares of high-carbon, low-skilled employment. These jobs are highly spatially concentrated around resource-extraction

In this comparison, we use new postings in all low-skilled low-carbon occupations, rather than restricting the pool to the 2 key low-carbon manual occupations identified in section 2.5.

centers including Wyoming, West Virginia, Oklahoma, Texas and the Appalachian region, echoing previous findings (Weber, 2020; Popp et al., 2021). In contrast, low-carbon, low-skilled vacancies are more dispersed (Figure 4A), consistent with the predominance of construction and installation roles (see Appendix Table H.6) and with findings that clean-energy hiring often occurs in licensed/certified trades with shorter formal-education requirements and comparatively strong wage floors (Muro et al., 2019b).

Locational Gini coefficient estimates are roughly twice as high for high-carbon (0.69) as for low-carbon (0.34) ads (Appendix Table H.1). In terms of spatial overlap, we find a positive, statistically significant correlation between the share of high-carbon employment and low-carbon job-ad shares (Appendix Table H.2). Weighted estimates, by ad count or population, imply that a 1% increase in the high-carbon employment share is associated with a 0.07% increase in the low-carbon job ad share. As a robustness check, we also compare flows to flows (low- and high-carbon job ads) and obtain similar patterns (Appendix Table H.3).

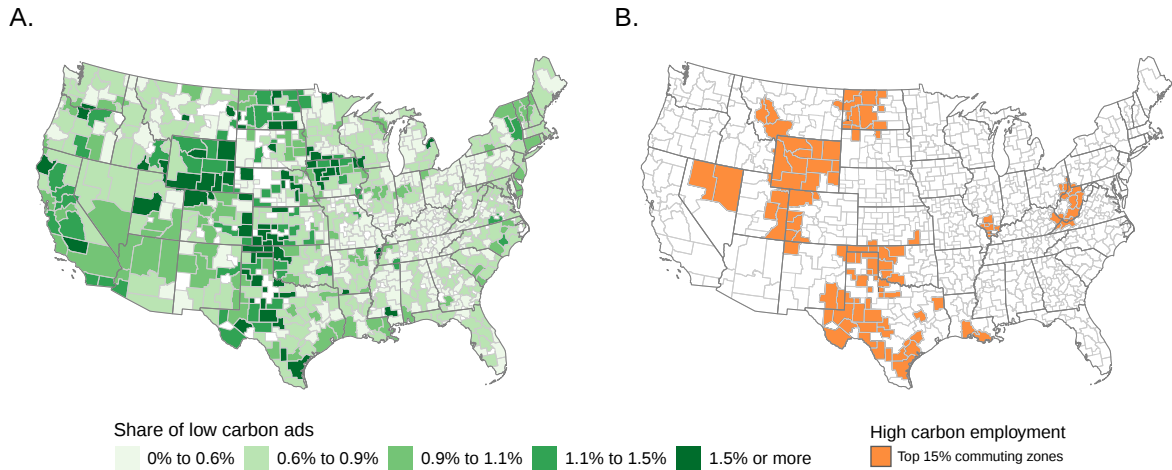


Figure 4: Spatial distribution of (A) low-carbon vacancies and (B) high-carbon employment in low skilled occupations

Notes: These maps show the intensity of low and high-carbon jobs by commuting zone, averaged over the period 2010-2019, for all low-skilled occupations (SOCs 31 to 53). Panel A shows the average share of low-carbon job vacancies; panel B shows the the top 15% commuting zones with the highest shares of high-carbon employment. *Source:* Lightcast and BLS.

To benchmark magnitude, we compare this correlation to the distribution of spatial correlations between shares of generic ads for any two 6-digit occupations within SOC 47 (Construction & Extraction) (Appendix Figure H.2). The correlation between low-carbon ads and high-carbon employment exceeds 83% of within-SOC-47 correlations, and is larger than prior estimates using solar and wind sectors (Curtis and Marinescu, 2023), thus sug-

Appendix Figure H.1 shows the spatial distribution of high-carbon job postings which instead, over-represents growing jobs, for example in fracking.

As detailed in the notes of Table H.2, we regress the log transformed share of low-carbon jobs on log transformed share of high-carbon jobs by commuting zone, using the $\log(1+x)$ transformation in order to avoid dropping the CZ with zero values. In contrast, Curtis and Marinescu (2023) regresses the share of high-carbon jobs

gests that the rise in low-carbon jobs could to some degree improve job finding rates of displaced workers from the transition and lower reallocation costs.

However, we also find that while high-carbon employment in the U.S. concentrate in poorer regions, low-carbon job creation is more prevalent in wealthier areas. Specifically, a 1% increase in average per capita income is associated with an 0.2% increase in the low-carbon ad share (Tables H.4) and a 0.1% fall in high-carbon ads (Table H.5). This indicates that the low-carbon transition may exacerbate regional inequalities, raising equity concerns consistent with Popp et al. (2021) and with evidence that geographic frictions constrain transitions (Lim et al., 2023).

To avoid the persistent regional scarring seen in past deindustrialization episodes (Autor et al., 2016, 2021), these patterns point to the value of targeted, place-based interventions alongside occupation-specific reskilling (see also Muro et al., 2019b; Bartik, 2020; Rodrik and Stantcheva, 2021). While fossil-fuel communities may attract some green job creation, further research on worker transitions—and on the design of effective place-based support—remains warranted.

7 Conclusions

We develop a transparent, skill-based methodology to identify low-carbon jobs within standard occupational groups and use it to provide the first job-level assessment of skill, wage, and spatial gaps associated with the energy transition. By leveraging text from established green classifications and applying NLP to a near-universe of U.S. online vacancies (2010–2019), we isolate low-carbon roles even within narrowly defined occupations and firms, and cross-validate the resulting series against task-based measures. Our approach is flexible, and can be adapted to monitor evolving low-carbon skill needs and to quantify reallocation frictions at varied spatial and sectoral scales, or for any technology types.

Three results stand out from our analysis. First, low-carbon jobs systematically demand more—and more diverse—skills than comparable non-low-carbon jobs in the same occupation (and firm), with larger within-occupation gaps than occupation-level analyses imply. These gaps are highly occupation-specific: STEM roles tend to deepen core capabilities, whereas business-oriented roles diversify beyond their occupational core.

Second, returns to skill complexity are higher in low-carbon roles, yet the associated wage premia are modest and declining once occupation and firm heterogeneity are controlled for—implying that earlier estimates overstated green premia to the extent they did not

(not log transformed) on the log transformed share of low-carbon jobs, excluding the CZ with zero values ($\log(x)$). When we replicate this specification, the coefficient is 0.006*** for the unweighted specification, and 0.007*** if excluding CZ without high-carbon employment shares, exceeding the 0.004 found in Curtis and Marinescu (2023).

net out firm wage differentials. The contrast with the higher, more persistent premia in high-carbon jobs underscores a potential attractiveness gap that policy must address.

Third, the geography of transition is uneven. High-carbon employment remains concentrated in resource-extraction regions, while low-carbon hiring is more dispersed but relatively stronger in wealthier areas. We document a positive yet modest spatial correlation between incumbent high-carbon employment and emerging low-carbon vacancies, consistent with location frictions that impede job reallocation even where skills overlap.

Taken together, our transparent methodology and detailed analysis substantially improves the evidence on skills and wage gaps. Embedding such evidence in economic modeling tools can improve the calibration of transition costs and inform the sequencing of climate, industrial, and workforce policies. Our results provide a stronger foundation for designing comprehensive policy frameworks, including more nuanced insights. For example, because the transition raises skill demands within occupations, generic upskilling is unlikely to be cost-effective; targeted, occupation-specific retraining that distinguishes specialization from diversification needs will be required ([OECD, 2023](#)). The modest and falling low-carbon premia suggest complementary policies that improve job quality and career ladders in low-carbon firms and projects. Finally, spatial frictions may warrant place-based strategies that co-locate training and investment with at-risk communities to curb reallocation costs and regional scarring.

References

- Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.
- Acemoglu, D. (2002). Directed technical change. *The Review of Economic Studies*, 69(4):781–809.
- Acemoglu, D. and Autor, D. (2011). Chapter 12 - skills, tasks and technologies: Implications for employment and earnings. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, volume 4, pages 1043 – 1171. Elsevier.
- Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2020). Ai and jobs: Evidence from online vacancies. Technical report, National Bureau of Economic Research.
- Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: evidence from online vacancies. *Journal of Labor Economics*, 40(S1):S293–S340.
- Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., and Rahwan, I. (2018). Unpacking the polarization of workplace skills. *Science advances*, 4(7):eaao6030.
- Aldy, J. E. (2013). Policy monitor a preliminary assessment of the american recovery and reinvestment act’s clean energy package. *Review of Environmental Economics and Policy*, 7(1):136–155.
- Alekseeva, L., Azar, J., Giné, M., Samila, S., and Taska, B. (2021). The demand for ai skills in the labor market. *Labour Economics*, 71:102002.
- Anderson, K. A. (2017). Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences*, 114(48):12720–12724.
- Antoni, M., Janser, M., and Lehmer, F. (2015). The hidden winners of renewable energy promotion: Insights into sector-specific wage differentials. *Energy Policy*, 86:595–613.
- Apostel, A. and Barlund, M. (2024). Measuring and characterising green jobs: A literature review. *Energy Research & Social Science*, 111:103477.
- Atalay, E., Phongthientham, P., Sotelo, S., and Tannenbaum, D. (2020). The evolution of work in the united states. *American Economic Journal: Applied Economics*, 12(2):1–34.
- Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. (2022). New frontiers: The origins and content of new work, 1940–2018. Technical report, National Bureau of Economic Research.
- Autor, D., Dorn, D., and Hanson, G. H. (2021). On the persistence of the china shock. Technical report, National Bureau of Economic Research.
- Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8(1):205–240.
- Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.
- Azar, J., Marinescu, I., Steinbaum, M., and Taska, B. (2020). Concentration in us labor markets: Evidence from online vacancy data. *Labour Economics*, 66:101886.
- Banfi, S. and Villena-Roldan, B. (2019). Do high-wage jobs attract more applicants? directed search evidence from the online labor market. *Journal of Labor Economics*, 37(3):715–746.

- Bartik, T. J. (2020). Using place-based jobs policies to help distressed communities. *The Journal of Economic Perspectives*, 34(3):99–127.
- Becker, R. A. and Shadbegian, R. J. (2009). Environmental Products Manufacturing: A Look inside the Green Industry. *The B.E. Journal of Economic Analysis & Policy*, 9(1):1–25.
- Bluedorn, J., Hansen, N.-J., Noureldin, D., Shibata, I., and Tavares, M. M. (2023). Transitioning to a greener labor market: Cross-country evidence from microdata. *Energy Economics*, 126:106836.
- Bone, M., González Ehlinger, E., and Stephany, F. (2025). Skills or degree? the rise of skill-based hiring for ai and green jobs. *Technological Forecasting and Social Change*, 214:124042.
- Bontadini, F. and Vona, F. (2023). Anatomy of green specialisation: Evidence from eu production data, 1995–2015. *Environmental and Resource Economics*, pages 1–34.
- Bouguettaya, A., Yu, Q., Liu, X., Zhou, X., and Song, A. (2015). Efficient agglomerative hierarchical clustering. *Expert Systems with Applications*, 42(5):2785–2797.
- Bowen, A., Kuralbayeva, K., and Tipoe, E. L. (2018). Characterising green employment: The impacts of ‘greening’ on workforce composition. *Energy Economics*, 72:263 – 275.
- Calel, R. and Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the european carbon market. *Review of Economics and Statistics*, 98(1):173–191.
- Campos, R., Mangaravite, V., Pasquali, A., Jorge, A., Nunes, C., and Jatowt, A. (2020). Yake! keyword extraction from single documents using multiple local features. *Information Sciences*, 509:257–289.
- Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly journal of economics*, 128(3):967–1015.
- Carley, S. and Konisky, D. M. (2020). The justice and equity implications of the clean energy transition. *Nature Energy*, 5(8):569–577.
- Castellanos, K. and Heutel, G. (2024). Unemployment, labor mobility, and climate policy. *Journal of the Association of Environmental and Resource Economists*, 11(1):1–40.
- Chen, S. (2022). Green investors and green transition efforts: Talk the talk or walk the walk? Available at SSRN 4254894.
- Chetty, R., Friedman, J. N., and Stepner, M. (2024). The economic impacts of covid-19: Evidence from a new public database built using private sector data. *The Quarterly Journal of Economics*, 139(2):829–889.
- Consoli, D., Marin, G., Marzucchi, A., and Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5):1046–1060.
- Curtis, E. M. (2018). Who loses under cap-and-trade programs? the labor market effects of the nox budget trading program. *Review of Economics and Statistics*, 100(1):151–166.
- Curtis, E. M. and Marinescu, I. (2022). Green energy jobs in the us: What are they, and where are they? Working Paper 30332, National Bureau of Economic Research.
- Curtis, E. M. and Marinescu, I. (2023). Green energy jobs in the united states: What are they, and where are they? *Environmental and Energy Policy and the Economy*, 4:202–237.

- Curtis, E. M., O’Kane, L., and Park, R. J. (2023). Workers and the green-energy transition: Evidence from 300 million job transitions. Working Paper 31539, National Bureau of Economic Research.
- Davis, S. J., Faberman, R. J., and Haltiwanger, J. (2012). Labor market flows in the cross section and over time. *Journal of monetary economics*, 59(1):1–18.
- Dechezleprêtre, A., Nachtigall, D., and Venmans, F. (2023). The joint impact of the european union emissions trading system on carbon emissions and economic performance. *Journal of Environmental Economics and Management*, 118:102758.
- Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.
- Deming, D. and Noray, K. (2020). Earnings dynamics, changing job skills, and stem careers. *The Quarterly Journal of Economics*, 135(4):1965–2005.
- Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640.
- Deming, D. J. (2023). Chapter 6 - multidimensional human capital and the wage structure. volume 7 of *Handbook of the Economics of Education*, pages 469–504. Elsevier.
- Deschenes, O. (2011). Climate policy and labor markets. In *The design and implementation of US climate policy*, pages 37–49. University of Chicago Press.
- Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., and Lewis, P. (2009). Greening of the world of work: Implications for o* net®-soc and new and emerging occupations.
- EBRD (2023). Transition report 2023-24: Transitions big and small. Technical report, EBRD.
- Egli, F., Johnstone, N., and Menon, C. (2015). Identifying and inducing breakthrough inventions: An application related to climate change mitigation. *OECD Science, Technology and Industry Working Papers*, (2015/04).
- Elliott, R. J., Kuai, W., Maddison, D., and Ozgen, C. (2024). Eco-innovation and (green) employment: A task-based approach to measuring the composition of work in firms. *Journal of Environmental Economics and Management*, 127:103015.
- Elliott, R. J. and Lindley, J. K. (2017). Environmental jobs and growth in the united states. *Ecological Economics*, 132:232–244.
- Fabra, N., Gutiérrez Chacón, E., Lacuesta, A., and Ramos, R. (2023). Do renewable energies create local jobs? *Available at SSRN 4579987*.
- Fankhauser, S., Bowen, A., Calel, R., Dechezleprêtre, A., Grover, D., Rydge, J., and Sato, M. (2013). Who will win the green race? in search of environmental competitiveness and innovation. *Global environmental change*, 23(5):902–913.
- Frattoni, F. F., Vona, F., and Bontadini, F. (2024). Does green re-industrialization pay off? impacts on employment, wages and productivity.
- Gabe, T. M. and Abel, J. R. (2012). Specialized knowledge and the geographic concentration of occupations. *Journal of Economic Geography*, 12(2):435–453.

- Gathmann, C. and Schönberg, U. (2010). How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1):1–49.
- Glachant, M. and Dechezleprêtre, A. (2016). What role for climate negotiations on technology transfer? *Climate Policy*, 0(0):1–15.
- Greenstone, M. (2002). The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures. *Journal of Political Economy*, 110(6):1175–1219.
- Güvenen, F., Kuruscu, B., Tanaka, S., and Wiczer, D. (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, 12(1):210–244.
- Hafstead, M. A. and Williams III, R. C. (2018). Unemployment and environmental regulation in general equilibrium. *Journal of Public Economics*, 160:50–65.
- Hanson, G. H. (2023). Local labor market impacts of the energy transition: Prospects and policies. Technical report, National Bureau of Economic Research.
- Haywood, L., Janser, M., and Koch, N. (2024). The welfare costs of job loss and decarbonization: Evidence from germany’s coal phaseout. *Journal of the Association of Environmental and Resource Economists*, 11(3):577–611.
- Hershbein, B. and Kahn, L. B. (2018a). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–72.
- Hershbein, B. and Kahn, L. B. (2018b). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–72.
- Iammarino, S., Rodriguez-Pose, A., and Storper, M. (2019). Regional inequality in europe: evidence, theory and policy implications. *Journal of economic geography*, 19(2):273–298.
- IMF (2022). World economic outlook: War sets back the global recovery. Technical report, International Monetary Fund.
- Kahn, M. E. and Mansur, E. T. (2013). Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics*, 101(C):105–114.
- Kambourov, G. and Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1):63–115.
- Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, 107(1):35–78.
- Kruse, T., Dellink, R., Chateau, J., and Agrawala, S. (2017). Employment implications of green growth: Linking jobs, growth, and green policies. *OECD Report for The G7 Environment Ministers*.
- Kuai, W., Elliott, R. J., Okubo, T., and Ozgen, C. (2025). Estimating the green wage premium. Technical report, IZA Discussion Papers.
- Lancaster, V. A., Mahoney-Nair, D., and Ratcliff, N. (2021). Review of burning glass job-ad data. Proceedings of the Biocomplexity Institute 2021-013, Biocomplexity Institute.
- Lim, J., Aklin, M., and Frank, M. R. (2023). Location is a major barrier for transferring us fossil fuel employment to green jobs. *Nature Communications*, 14(1):5711.

- Lin, J. (2011). Technological adaptation, cities, and new work. *Review of Economics and Statistics*, 93(2):554–574.
- Marin, G., Marino, M., and Pellegrin, C. (2018). The impact of the european emission trading scheme on multiple measures of economic performance. *Environmental and Resource Economics*, 71(2):551–582.
- Marin, G. and Vona, F. (2019). Climate policies and skill-biased employment dynamics : evidence from EU countries. *Journal of Environmental Economics and Management*, 98:102253.
- Martin, R., De Preux, L. B., and Wagner, U. J. (2014). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, 117:1–14.
- Meyer, A. G. (2022). Do economic conditions affect climate change beliefs and support for climate action? evidence from the us in the wake of the great recession. *Economic Inquiry*, 60(1):64–86.
- Mincer, J. (1974). Schooling and earnings. In *Schooling, experience, and earnings*, pages 41–63. NBER.
- Morgenstern, R. D., Pizer, W. A., and Shih, J.-S. (2002). Jobs versus the environment: an industry-level perspective. *Journal of environmental economics and management*, 43(3):412–436.
- Muro, M., Tomer, A., Shivaram, R., and Kane, J. (2019a). Advancing inclusion through clean energy jobs. Technical report, Brookings Institution, <https://www.brookings.edu/articles/advancing-inclusion-through-clean-energy-jobs/>.
- Muro, M., Tomer, A., Shivaram, R., and Kane, J. (2019b). Advancing inclusion through clean energy jobs.
- Muttitt, G. and Kartha, S. (2020). Equity, climate justice and fossil fuel extraction: principles for a managed phase out. *Climate Policy*, 20(8):1024–1042.
- Neffke, F. M. (2019). The value of complementary co-workers. *Science advances*, 5(12):eaax3370.
- OECD (2023). *OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition*. OECD Publishing, Paris.
- OECD (2024). *OECD Employment Outlook 2024: The Net-Zero Transition and the Labour Market*. Technical report, OECD, OECD Publishing, Paris, <https://doi.org/10.1787/ac8b3538-en>.
- OECD and CEDEFOP (2014). *Greener Skills and Jobs*. OECD Publishing, Paris.
- Poletaev, M. and Robinson, C. (2008). Human capital specificity: evidence from the dictionary of occupational titles and displaced worker surveys, 1984–2000. *Journal of Labor Economics*, 26(3):387–420.
- Popp, D., Vona, F., Gregoire-Zawilski, M., and Marin, G. (2024). The next wave of energy innovation: Which technologies? which skills? *Review of Environmental Economics and Policy*, 18(1):000–000.
- Popp, D., Vona, F., Marin, G., and Chen, Z. (2021). The employment impact of a green fiscal push: Evidence from the american recovery and reinvestment act. *Brookings Papers on Economic Activity, Fall*. 1-49.

- Reimers, N. and Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.
- Rodrik, D. and Stantcheva, S. (2021). Fixing capitalism’s good jobs problem. *Oxford Review of Economic Policy*, 37(4):824–837.
- Song, J., Price, D. J., Guvenen, F., Bloom, N., and Von Wachter, T. (2019). Firming up inequality. *The Quarterly journal of economics*, 134(1):1–50.
- Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of labor economics*, 24(2):235–270.
- Stephany, F. and Teutloff, O. (2024). What is the price of a skill? the value of complementarity. *Research Policy*, 53(1):104898.
- Strietska-Ilina, O., Hofmann, C., Haro, M. D., and Jeon, S. (2012). *Skills for green jobs: A global view*. International Labour Organisation Geneva.
- Tomer, Adie, J. W. K. and George, C. (2021). How renewable energy jobs can uplift fossil fuel communities and remake climate politics. Technical report, Brookings.
- Tsvetkova, A., D’Amico, E., Lembcke, A., Knutsson, P., and Vermeulen, W. (2024). How well do online job postings match national sources in large english speaking countries?: Benchmarking lightcast data against statistical sources across regions, sectors and occupations. Local Economic and Employment Development (LEED) Papers 2024/01, OECD, OECD Publishing, Paris.
- U.S. Energy Information Administration (2021). U.S. energy-related carbon dioxide emissions, 2020. Technical report, U.S. EIA.
- Valero, A., Li, J., Muller, S., Nguyen-Tien, V., and Draca, M. (2021). Are ‘green’ jobs good jobs? how lessons from the experience to-date can inform labour market transitions of the future. Technical report, Grantham Research Institute on Climate Change and the Environment.
- Vona, F. (2019). Job losses and political acceptability of climate policies: why the ‘job-killing’ argument is so persistent and how to overturn it. *Climate Policy*, 19(4):524–532.
- Vona, F. (2021). *Labour markets and the green transition: a practitioner’s guide to the task based approach*, volume 126681. Publications Office of the European Union.
- Vona, F., Marin, G., and Consoli, D. (2019). Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014. *Journal of Economic Geography*, 19(5):1021–1048.
- Vona, F., Marin, G., Consoli, D., and Popp, D. (2018). Environmental Regulation and Green Skills: An Empirical Exploration. *Journal of the Association of Environmental and Resource Economists*, 5(4):713–753.
- Walker, W. R. (2011). Environmental regulation and labor reallocation: Evidence from the Clean Air Act. *The American Economic Review*, 101(3):442–447.
- Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *The Quarterly journal of economics*, 128(4):1787–1835.
- Weber, J. G. (2020). How should we think about environmental policy and jobs? an analogy

- with trade policy and an illustration from us coal mining. *Review of Environmental Economics and Policy*, 14(1):44–66.
- Whittard, D., Bradley, P., Phan, V., and Ritchie, F. (2025). Working towards an environmentally sustainable and equitable future? new evidence on green jobs from linked administrative data in the uk. *Journal of Cleaner Production*, page 145025.
- Yip, C. M. (2018). On the labor market consequences of environmental taxes. *Journal of Environmental Economics and Management*, 89:136–152.
- Zaussinger, F., Schmidt, T. S., and Egli, F. (2025). Skills-based and regionally explicit labor market exposure to the low-carbon transition in europe. *Joule*.
- Zhang, Z., Zheng, C., Xiao, Z., and Zhu, K. (2025). Occupational carbon footprints and exposure to climate transition risks. *Nature Communications*, 16(1):5886.

Supplemental Appendix

Appendix A Representativeness of the Lightcast dataset

Table A.1: Representativeness of Lightcast ads dataset vs. BLS employment

SOC major group	Ad count	Unweighted ad share	BLS employment share
15 - Computer and Mathematical	26,454,718	12.3%	2.9%
11 - Management	26,436,466	12.3%	5.0%
29 - Healthcare Practitioners and Technical	25,852,786	12.0%	5.9%
13 - Business and Financial Operations	15,445,834	7.2%	5.1%
17 - Architecture and Engineering	7,135,965	3.3%	1.8%
25 - Education, Training, and Library	5,579,005	2.6%	5.8%
27 - Arts, Design, Entertainment, Sports, and Media	5,311,202	2.5%	1.3%
21 - Community and Social Service	2,541,329	1.2%	1.4%
19 - Life, Physical, and Social Science	2,280,480	1.1%	0.8%
23 - Legal	1,660,423	0.8%	0.8%
41 - Sales and Related	27,083,405	12.6%	10.6%
43 - Office and Administrative Support	23,623,473	11.0%	16.1%
53 - Transportation and Material Moving	8,513,938	4.0%	6.9%
35 - Food Preparation and Serving Related	7,786,029	3.6%	9.1%
49 - Installation, Maintenance, and Repair	7,060,358	3.3%	3.9%
51 - Production	5,766,857	2.7%	6.6%
31 - Healthcare Support	4,795,236	2.2%	2.9%
39 - Personal Care and Service	3,866,793	1.8%	3.1%
37 - Building and Grounds Cleaning and Maintenance	2,895,529	1.3%	3.2%
33 - Protective Service	2,395,055	1.1%	2.5%
47 - Construction and Extraction	2,384,535	1.1%	3.9%
45 - Farming, Fishing, and Forestry	152,616	0.1%	0.3%

Appendix B Identifying low-carbon skills and jobs using job ads data

B.1 Implementation of the low-carbon skills selection algorithm

This section details the implementation of our data- and NLP-driven methodology for identifying low-carbon skills, leveraging three well-established “green” textual sources: (i) green tasks in the Occupational Information Network (O*NET), (ii) Cooperative Patent Classification (CPC) group titles in class Y02, and (iii) trade product categories related to green transport in PRODCOM as identified by [Bontadini and Vona \(2023\)](#).

Let T index the three source classifications. Each T consists of items $t \in T$ (O*NET task descriptions, CPC group titles, or PRODCOM product names), and we partition items into a green subset T_g and a non-green subset T_{ng} .

Step 1: Keyword extraction from textual sources

We extract keywords that distinguish low-carbon content from generic content within each source. For each item $t \in T$ (task from O*NET, CPC technology title from class Y02, or transport product category title from PRODCOM), we run YAKE ([Campos et al., 2020](#)) to extract uni- and bi-grams k together with item-specific relevance scores $\sigma_{k,t}^T \in [0, 1]$. We then aggregate to the subset level using a continuous analogue of TF-IDF. Denote by $n_{k,o}^T$ the number of items in subset $o \in \{g, ng\}$ from which k was extracted; we define

$$\sigma_{k,o}^T = \log(n_{k,o}^T) \frac{\sum_{t \in T_o} \sigma_{k,t}^T}{n_{k,o}^T}$$

To isolate low-carbon content we work with the contrastive score

$$\Delta\sigma_k^T = \sigma_{k,g}^T - \sigma_{k,ng}^T,$$

taking $\sigma_{k,ng}^T = 0$ when k never appears in T_{ng} . For each source T , we examine the distribution of $\Delta\sigma_k^T$ and set a source-specific threshold τ^T at the discontinuity points ([Appendix Figure B.1](#)).

Inclusion criterion: k enters the low-carbon keyword set iff $\Delta\sigma_k^T > \tau^T$. With our baseline thresholds this yields $n_K = 35$ low-carbon keywords ([Appendix Table B.1](#)). Sensitivity to τ^T is reported in [Section B.2](#).

Step 2: Classify skills using three complementary signals

O*NET provides information about the specific task contents of narrowly defined occupations (867 BLS Standard Occupational Classification (SOC) occupations). The 2009 Green Economy Program marked tasks that are “green”, which covers not only climate change-related tasks but also tasks that contribute toward non-climate environmental problems such as waste management, remediation activities, and activities associated with local air and water pollution. See <https://www.onetcenter.org/reports/GreenTask.html> for more details.

The CPC defines the Y02 class as “Technologies or applications for mitigation or adaptation against climate change”.

Equivalently: when a keyword is only extracted from green items, its non-green relevance is set to zero.

We classify Lightcast skills as low-carbon using three independent signals, applied to the universe of $\sim 16,000$ skills.

Signal A: Contrastive frequency in source texts (keyword-independent). For each skill s and source T , we count occurrences in the green and non-green subsets, $n_{s,g}^T$ and $n_{s,ng}^T$, based on direct lexical matches between the Lightcast skill name and items $t \in T$.

Inclusion criterion: s is flagged as low-carbon by source T if $n_{s,ng}^T = 0$ and $n_{s,g}^T$ lies in the top quintile of the T -specific distribution. This signal contributes 46 skills.

Signal B: Direct lexical match to low-carbon keywords. We compare the Lightcast skill inventory to the keyword set from Step 1.

Inclusion criterion: s is flagged if its name is an exact (case-insensitive) string match to any keyword k . This contributes 214 skills.

Signal C: Semantic match to low-carbon keywords. To bridge vocabulary differences between sources and Lightcast, we compute sentence-transformer embeddings (Reimers and Gurevych, 2019) for each skill s and each keyword k , and obtain pairwise semantic proximity scores $\mu_{s,k}$. To identify the skills most closely related to the low-carbon keywords, we aggregate these scores into a single proximity score per skill μ_s designed to balance the similarity to all low-carbon keywords and the high similarity with a specific low-carbon keyword:

$$\mu_s = \left(\frac{\sum_k \mu_{s,k}}{n_K} \right) \left(\max_k \mu_{s,k} - \frac{\sum_k \mu_{s,k}}{n_K} \right)$$

Inclusion criterion: Skill s is flagged if μ_s lies in the top percentile across all skills. This contributes 35 skills.

This step yields an initial set of 295 unique low-carbon skills after taking the union of the sets of low-carbon skills yielded by signals A, B and C. Sensitivity tests to definitions of the inclusion criteria in each signal are presented in Tables I.1 and I.2.

Step 3: Coverage extension through semantic clustering

To improve coverage of near-duplicate or closely related skills, we cluster the full Lightcast inventory using agglomerative hierarchical clustering on skill embeddings (Bouguettaya et al., 2015). The pairwise Euclidian distance in the embeddings space is compute for all pair skills. Groups of skills whose embeddings are located within a sphere of a radius smaller than a given threshold are grouped in the same semantic cluster. This yields 6,668 semantically coherent clusters of skills. Sensitivity to the clustering threshold is presented in Tables I.1 and I.2.

Given the structure of the CPC patent classification, core climate technologies (e.g., solar and wind, EVs) often appear outside Y02; for CPC only, we therefore relax the $n_{s,ng}^T = 0$ requirement.

Inclusion criterion: any skill belonging to a cluster that contains at least one low-carbon skill from Step 2 is also classified as low-carbon. This adds a further 98 low-carbon skills.

Step 4: Exclusion for decarbonization focus, and of false positives

To sharpen the focus on decarbonization and remove spurious matches, we implement a targeted exclusion list comprising: (i) green but non-climate activities (e.g., water treatment, environmental remediation), (ii) generic energy skills not specific to decarbonization, and (iii) fossil-fuel-related skills that are semantically close to low-carbon content. We operationalize this via a small set of excluded Lightcast skill categories and excluded keywords (Appendix Table B.2). We then manually drop a documented set of brand-name false positives (e.g., *Solaris*, *Sungard*, *Greenplum*) listed in Appendix Table B.3.

Our final algorithm yields 389 low-carbon skills, which we refer to as *low-carbon job identifiers* (Appendix Tables B.5–B.7). A job posting is classified as low-carbon if it contains at least one such identifier. Robustness to alternative cut-offs at each step is reported in Sections B.2 and I.

B.2 Sensitivity of low-carbon skills selection to threshold choices

Using unsupervised scoring tools such as keyword extraction and semantic matching necessitates choosing cutoff levels. To assess our choice of thresholds, we first check the sensitivity of our skills selection against the thresholds. Further, sensitivity analysis demonstrate that our main results are robust to threshold choices.

Our low-carbon skill selection algorithm includes four thresholds and we assess how adjusting these changes the skills considered low-carbon. Overall, the following results give us confidence in our choice of thresholds. First, for each textual source T , we adjust the cutoff levels τ_g^T for the relevance score in Step 1 by 10% in both directions. As shown in Table I.1, relaxing the threshold by 10% adds two extra skills related to Wastewater (not relevant for low-carbon), while tightening the threshold by 10% instead removes 82 skills, that are relevant for the low-carbon transition, thus validating our choice to select τ_g^T based on discontinuities in the distribution. Second, we test moving the semantic proximity score threshold (top 1%) in Step 2 to 0.5% and 1.5%. The former removes 13 skills while the latter adds 25 skills, including some very generic skills unrelated to low-carbon (e.g. International Transportation Services) but also those relevant for low-carbon (e.g. Wind Energy Project Management). Third, we adjust the direct text match frequency threshold in Step 2 (top quintile) by 10% in each direction. Relaxing the threshold by 10% adds 27 extra skills that are largely related to non-low-carbon environmental activities like Biodiversity and Water, while tightening the threshold by 10% instead removes 23 skills, many of which are relevant for the low-carbon transition (e.g., Electric Vehicles and Biofuel-related). Finally, we test the sensitivity to the number of cluster in the semantic

clustering in step 2, by adjusting the threshold. Increasing it by 10% increases the number of low-carbon skills by 24, or 6%), while reducing it by 10% decreases low-carbon skills by 21, or 5.2%.

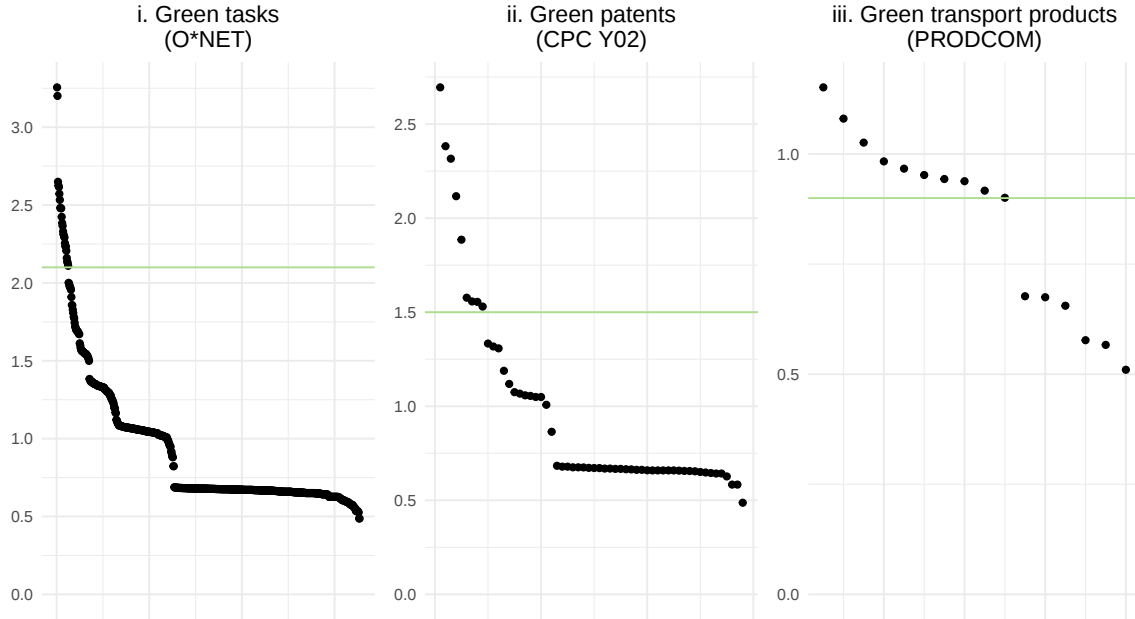


Figure B.1: Distribution of YAKE scores and thresholds for low-carbon keyword inclusion

Notes: Each panel corresponds to one of the three textual sources T . They represent the distribution of the green relevance score $\sigma_{k,g}^T$ as defined in Step 2 for all keyword candidates (monogram or bigram) extracted by the YAKE algorithm from the green subset of source T . Thus, each dot is a keyword candidate. Keywords that were also extracted from the corresponding non-green subsets are excluded according to Step 2's inclusion criteria. The green horizontal lines represent the selected threshold τ_g^T in each source T .

Table B.1: List of extracted low-carbon keywords

alternative energy	fuel cell	rail
bicycle	gas collection	railway
biomass	geothermal	renewable energy
carbon emission	ghg	self-propelled
change mitigation	green	service vehicle
climate change	green product	solar
coach	greenhouse gas	solar energy
emissions mitigation	hydroelectric	technologies relating
enabling technology	indirect contribution	tramway
energy efficiency	landfill gas	van
energy efficient	locomotive	wind turbine
energy management	photovoltaic	

Table B.2: Lightcast skill categories and keywords excluded from the low-carbon skills donor pool

Excluded Lightcast skill categories	
Fossil fuel extraction	Gas Drilling, Geology Software, Hydraulic Fracturing, Natural Gas, Oil Drilling, Oil Refining, Oil Reservoirs, Oil Well Intervention, Oil Wells, Petroleum Science
Conventional energy production	Energy Management, Energy Solutions, Electrical Power, Nuclear Energy, Power Plant
Non-climate environmental	Ecology, Environmental Geology, Geology Software, Hazardous Waste Management, Resource Management and Restoration, Waste Management, Water Supply, Water Testing and Treatment
Excluded keywords	<i>power, generation, environment, monitoring</i> except if match with <i>renewable, solar</i> and <i>wind</i>

Table B.3: False-positives skills matched by the NLP selection algorithm

IT	Consumer Electronics, Greenplum, Green Hills Integrity, Network File System (NFS), Solarwinds, Six Sigma, Sungard, Web Development
Energy	Electrical Control, Electric Motors, Energy Sales, Gas Exchange, Gas Management
Policy	Benefits Analysis, Human Resources, Investigative R&D, Policy Recommendation, Site Assessments, Technology Research
Transport	Aerospace Engineering, Bridge, Motor Vehicle Operation, Passenger Vans, Transportation Systems, Vehicle Systems

Table B.4: Skills re-integrated to test the robustness of results to the inclusion of gray and non-climate green skills

CCS-related	Geology Software
Nuclear	Nuclear Energy
Non-climate green	Ecology, Environmental Geology, Hazardous Waste Management, Resource Management and Restoration, Waste Management, Water Supply, Water Testing and Treatment

Table B.5: Low-carbon job identifiers/ low-carbon skills

Abatement Projects	Biomass Research	Emissions Control Systems
Air Emissions	Biomass Thermochemical Conversion	Emissions Inspection
Air Pollution Control	Biomass Transformation	Emissions Inventories
Air Quality Control	Blower Doors	Emissions Management
Air Quality Regulations	Building Performance	Emissions Mitigation
Air Quality Remediation	Carbon Accounting	Emissions Reduction
Air Quality Standards	Carbon Asset Management	Emissions Reduction Strategy
Alternative Energy	Carbon Emissions Reduction	Emissions Standards
Alternative Energy Design	Carbon Footprint	Emissions Testing
Alternative Energy Evaluation	Carbon Footprint Reduction	Energy - Efficient Systems
Alternative Fuel Vehicles	Carbon Management	Energy Conservation
Alternative Fuels	Carbon Offsets	Energy Conservation Measures
Automotive Energy Management	Carbon Reduction	Energy Conversion
Benefits Research	Clean Energy	Energy Cost Reduction
Bicycle Planning	Climate Analysis	Energy Efficiency
Bike Industry Knowledge	Climate Change	Energy Efficiency Analysis
Biodiesel	Climate Change Analysis	Energy Efficiency Assessment
Biodiesel Development	Climate Change Impact	Energy Efficiency Consultation
Biodiesel Industry Knowledge	Climate Change Mitigation Initiatives	Energy Efficiency Improvement
Biodiesel Production	Climate Change Policies	Energy Efficiency Products
Biodiesel Research	Climate Change Principles	Energy Efficiency Research
Biodiesel Technology	Climate Change Processes	Energy Efficiency Services
Biofuel Product Development	Climate Change Programs	Energy Efficiency Supervision
Biofuel Production	Climate Change Research	Energy Efficiency Technologies
Biofuels Applications	Climate Change Simulations	Energy Efficient Building
Biofuels Development	Climate Data Analysis	Energy Efficient Home Improvement
Biofuels Extraction	Climate Information	Energy Efficient Lighting
Biofuels Plant Safety	Climate Management Research	Energy Efficient Operations
Biofuels Processing	Climate Outreach	Energy Efficient Transportation
Biofuels Processing Equipment	Climate Policy	Energy Law
Biofuels Quality Assessment	Climate Research	Energy Loss Calculation
Biofuels Research	Climate Systems	Energy Loss Reduction
Biofuels Research and Development	Climate Theory	Energy Outreach
Biofuels Technology	Commercial Solar Projects	Energy Reduction
Biomass	Commercial Solar Sales	Energy Saving Products
Biomass Conversion	Concentrated Photovoltaic Technology	Energy Savings Calculations
Biomass Determination	Cooling Efficiency	Energy Supply Side Savings
Biomass Equipment	Cost-Benefit Studies	Energy-Efficient Appliances
Biomass Feedstock Measurement	Direct Methanol Fuel Cells	Equipment Effectiveness
Biomass Fuel Gasification Systems	Ecological Consulting	Equipment Efficiency
Biomass Gasification Processes	Efficient Transportation	Ethanol
Biomass Plant Equipment	Electric Vehicle	Ethanol Distillation
Biomass Pretreatment Evaluation	Electricity Regulation	Ethanol Recovery Methods
Biomass Processing Equipment	Emission Reduction Projects	Facility Improvement
Biomass Production	Emissions Analysis	Facility Remodeling
Abatement Projects	Biomass Research	
Air Emissions	Biomass Thermochemical Conversion	
Air Pollution Control	Biomass Transformation	
Air Quality Control	Blower Doors	
Air Quality Regulations	Building Performance	

Table B.6: Low-carbon job identifiers/ low-carbon skills (cont.)

Facility Renovation	Green Energy	Locomotive Safety Standards
Fuel Cell	Green Energy Marketing	Loose Insulation
Fuel Cell Analysis	Green Energy Promotion	Low Carbon Projects
Fuel Cell Applications	Green Job Development	Low Carbon Solutions
Fuel Cell Assembly	Green Manufacturing	Low Energy Buildings
Fuel Cell Design	Green Marketing	Methane Gas Collection System
Fuel Cell Development	Green Plumbing	Mitigation Projects
Fuel Cell Engineering	Green Plumbing Equipment Installation	Natural Lighting Systems
Fuel Cell Generator	Green Procurement	Optical Data Storage
Fuel Cell Modeling	Green Real Estate	Organic Photovoltaics (OPV)
Fuel Cell Performance Improvement	Green Retail	PV System Design and Drafting
Fuel Cell Research	Green Retrofitting	PVNS
Fuel Cell System Design	Green Roof Design	PVsyst
Fuel Cell Testing	Green Roof Installation	Performance Yield
Fuel Cell Testing Equipment	Green Roofing	Photovoltaic Mounting Solutions
Fuel Cell Theory	Green Stocks	Photovoltaic (PV) Energy Production
Fuel Cell Validation	Green Strategy	Photovoltaic (PV) Equipment
Fuel Cell Vehicles	Green Supplier	Photovoltaic (PV) Systems
Fuel Efficiency	Green Techniques	Photovoltaic Energy
Gas Collection	Green Technology	Photovoltaic Solutions
Gas Collection Equipment	Green Transportation	Photovoltaic System Design
Gas Collection Systems	Green Walls	Photovoltaic (PV) Module Evaluation
Geothermal	Greenhouse Gas	Pollution Control
Geothermal Energy Plants	Greenhouse Gas (GHG) Emissions	Pollution Control Equipment
Geothermal Heat Systems	Greenhouse Gas Accounting	Pollution Control Systems
Geothermal Loop Systems	Heating Efficiency	Pollution Prevention
Geothermal Plant Equipment	Heavy Rail	Pollution Regulation
Geothermal Plant Operations	Heavy Rail Transit Systems	Polymer Electrolyte Membrane Fuel Cells
Geothermal Production	High Speed Rail	Public Transit Operations
Geothermal Production Management	Industrial Ecology	Public Transit Systems
Geothermal Sales	Insulating Materials	Public Transportation System
Global Warming	Insulation	Rail Equipment Maintenance
Global Warming Pollution	Insulation Efficiency	Rail Equipment Repair
Green Architecture	Insulation Installation	Rail Industry Knowledge
Green Automotive Technologies	Landfill Design	Rail Operations
Green Building	Landfill Gas Collection	Rail Safety
Green Building Standards	Landfill Gas Collection System Operation	Rail-Track Laying
Green Certified Construction Practices	Landfill Inspection	Railroad Conducting
Green Chemistry	Landfill Operations	Railroad Design
Green Chemistry Methods	Light Rail	Railroad Engineering
Green Communities	Light Rail Transit Systems	Railroad Safety
Green Contractor	Lighting Systems	Railway Signaling
Green Design	Locomotive Engineering	Railway Systems
Green Distributor	Locomotive Inspection	Renewable Energy
Green Education	Locomotive Safety	Renewable Energy Consultation
Facility Renovation	Green Energy	
Fuel Cell	Green Energy Marketing	
Fuel Cell Analysis	Green Energy Promotion	
Fuel Cell Applications	Green Job Development	
Fuel Cell Assembly	Green Manufacturing	

Table B.7: Low-carbon job identifiers/ low-carbon skills (cont.)

Renewable Energy Development	Solar Module Assembly	Trams
Renewable Energy Equipment	Solar PV Generation Systems	Transit Systems
Renewable Energy Industry Knowledge	Solar PV Hot Water Heating Systems	Weatherization
Renewable Energy Installation	Solar Panel Assembly	Weatherization Installation
Renewable Energy Markets	Solar Panel Attachment	Wind Commissioning
Renewable Energy Supply	Solar Panel Fitting	Wind Consultation
Renewable Energy Systems	Solar Panels	Wind Energy Engineering
Renewable Resources	Solar Photovoltaic Business Development	Wind Energy Industry Knowledge
Residential Energy Conservation	Solar Photovoltaic Design	Wind Energy Operations
Residential Energy Efficiency	Solar Photovoltaic Engineering	Wind Energy Operations Management
Retrofitting	Solar Photovoltaic Installation	Wind Farm Analysis
Silicon Solar Cell	Solar Photovoltaic Panels	Wind Farm Construction
Smart Grid	Solar Photovoltaic Performance Improvement	Wind Farm Design
Smoke Emissions Reduction	Solar Photovoltaic Research	Wind Field Operations
Soil Tillers	Solar Photovoltaic Technology	Wind Generator Assembly
Solar Application	Solar Power Electrical Work	Wind Integration Studies
Solar Array Production Calculation	Solar Power Purchase Agreement Sales	Wind Power
Solar Boilers	Solar Power System Design	Wind Power Development
Solar Cell	Solar Products	Wind Turbine Construction
Solar Cell Design	Solar Purchasing Management	Wind Turbine Control System
Solar Cell Equipment	Solar Roofing System Installation	Wind Turbine Equipment
Solar Cell Manufacturing	Solar Roofs	Wind Turbine Equipment Testing
Solar Cell Manufacturing Equipment	Solar Sales	Wind Turbine Fabrication
Solar Collector Installation	Solar Sales Management	Wind Turbine Performance Improvement
Solar Consultation	Solar Start Ups	Wind Turbine Production
Solar Contractor	Solar Systems	Wind Turbine Service
Solar Design	Solar Technology	Wind Turbine Technology
Solar Development	Solar Thermal Installation	Wind Turbines
Solar Electric Installation	Solar Thermal Systems	Zero- Energy Buildings
Solar Energy	Solar and Wind Energy	
Solar Energy Components	Spray Foam (Insulation)	
Solar Energy Industry Knowledge	Storage Management Technologies	
Solar Energy Installation Management	Streetcars	
Solar Energy System Development	Sustainability Campaigns	
Solar Energy System Installation	Sustainability Consulting	
Solar Energy Systems	Sustainability Marketing	
Solar Energy Systems Engineering	Sustainable Architecture	
Solar Engineering	Sustainable Design	
Solar Equipment	Sustainable Energy	
Solar Farm	Sustainable Engineering	
Solar Heat Absorption Reduction	Sustainable Manufacturing	
Solar Heating	Sustainable Materials	
Solar Hot Water Heating Systems	Thermochemical Conversion	
Solar Installation	Thermochemical Research	
Solar Manufacturing	Tillage	
Renewable Energy Development	Solar Module Assembly	
Renewable Energy Equipment	Solar PV Generation Systems	
Renewable Energy Industry Knowledge	Solar PV Hot Water Heating Systems	
Renewable Energy Installation	Solar Panel Assembly	
Renewable Energy Markets	Solar Panel Attachment	

Table B.8: Top 50 low-carbon identifiers observed in job ads

Low carbon identifier	Ad count	Low carbon identifier	Ad count
Insulation	226,247	Transit Systems	24,469
Energy Efficiency	190,005	Pollution Control	24,326
Energy Conservation	151,033	Fuel Efficiency	24,003
Renewable Energy	150,605	Insulation Installation	23,948
Retrofitting	109,361	Green Building	23,798
Solar Energy	66,983	Fuel Cell	23,616
Climate Change	49,415	Public Transit Systems	22,537
Clean Energy	42,839	Electric Vehicle	22,392
Solar Sales	42,122	Equipment Effectiveness	21,774
Wind Turbines	40,848	Energy Reduction	21,686
Pollution Prevention	40,488	Alternative Fuels	21,507
Wind Power	39,313	Geothermal	18,448
Equipment Efficiency	38,109	Greenhouse Gas	17,757
Building Performance	37,053	Solar Installation	17,349
Air Emissions	36,787	Weatherization	17,013
Smart Grid	31,704	Sustainable Energy	16,088
Solar Panels	31,610	Energy Conservation Measures	15,357
Photovoltaic (PV) Systems	29,799	Solar Systems	15,068
Alternative Energy	29,668	Green Energy	14,848
Sustainable Design	28,336	Biomass	14,094
Air Pollution Control	28,197	Emissions Management	13,845
Emissions Testing	27,761	Facility Improvement	13,526
Ethanol	27,722	Rail Operations	12,309
Efficient Transportation	26,194	Solar Consultation	11,357
Light Rail	25,897	Locomotive Engineering	10,355

Table B.9: Example of low-carbon ads

Title	SOC	Location	Degree	Annual wage	Skills
Senior Planner	13-1121 - Meeting, Convention, and Event Planners	Upper Marlboro, Maryland	Master's	51k - 88k	Bicycle Planning , Editing, Environmental Science, Grant Applications, Planning, Transit-Oriented Development, Writing
Facilities Planner	17-1011 - Architects, Except Landscape and Naval	Tallahassee, Florida	Bachelor's	35k - 40k	Green Building , Budgeting, Capital Planning, Construction Management, Planning, Project Management, Spreadsheets, Urban Planning
Chemical Engineer	17-2041 - Chemical Engineers	Houston, Texas	Bachelor's	180k - 200k	Energy Efficiency , Business Acumen, Chemical Engineering, Performance Appraisals, Process Modeling, Project Management, Simulation, Technical Support
Printer/Electronics Technician	17-3023 - Electrical and Electronics Engineering Technicians	Denver, Colorado	Associate's	51k - 51k	Retrofitting , AC/DC Drives and Motors, Break/Fix, Computer Literacy, Description and Demonstration of Products, Fault Codes, Lifting Ability, Mechanical Repair, Microsoft Office, Printers, Repair, Troubleshooting
Post-Doctoral Research Scholar-Chemical Engineering	19-2011 - Astronomers	Richmond, Virginia	PhD	59k - 85k	Green Chemistry , Chemical Engineering, Chemistry, Communication Skills, Design of experiments (DOE), High-Performance Liquid Chromatography (HPLC), Lab Safety, Laboratory Safety And Chemical Hygiene Plan, Mentoring, Research, Teamwork / Collaboration, Writing
Lead Solar Installer	47-2231 - Solar Photovoltaic Installers	Rancho Cucamonga, California	High School	37k - 41k	Solar Installation , Customer Contact, Electrical Experience, Fall Protection, Operations Management, Physical Abilities, Roofing, Scheduling
Maintenance Mechanic	49-9099 - Installation, Maintenance, and Repair Workers, All Other	Battle Creek, Michigan	High School	19k - 26k	Energy Efficiency , Commercial Driving, Repair, Troubleshooting Technical Issues

Table B.10: High-carbon occupations (SOC codes) and sectors (NAICS codes)

SOC	17-2151	Mining and Geological Engineers
codes	17-2171	Petroleum Engineers
	47-5	Extraction Workers

NAICS	211	Oil and Gas Extraction
codes	2121	Coal Mining
	213111	Drilling Oil and Gas Wells
	213112	Support Activities for Oil and Gas Operations
	2212	Natural Gas Distribution
	23712	Oil and Gas Pipeline and Related Structures
	32411	Petroleum Refineries
	32412	Asphalt Paving, Roofing, and Saturated Materials
	324191	Petroleum Lubricating Oil and Grease Manufacturing
	4247	Petroleum and Petroleum Products Merchant
	44711	Gasoline stations with convenience stores
	44719	Other Gasoline Stations
	45431	Fuel dealers
	486	Pipeline Transportation

Appendix C Occupational shares of low- and high-carbon ads

Table C.2 reports the number of low-carbon ads and their employment-weighted share by 2-digit SOC occupation. While low-carbon jobs are found across a wide range of occupations (see also Figure C.1 for the evolution of the share of low-carbon ads by occupation and sectors (see Appendix Table C.4), five 2-digit SOC groups exhibit notably higher shares: Business & Finance (1.6%); Architecture & Engineering (4.1%); Life, Physical & Social Science (3.3%); Construction & Extraction (4.4%); Installation, Maintenance & Repair (2.6%).

A more granular examination at the 3-digit SOC level for high-skilled occupations (Table C.3) reveals substantial within-occupation heterogeneity. For instance, within the Business & Finance occupations (SOC 13), a high share of low-carbon ads is concentrated among Business Specialists (13-1). Within Life, Physical, & Social Science (SOC 19), Physical Scientists (19-2) stand out with a high share of 8%. In Architecture & Engineering (SOC 17), Architects, Engineers (17-2), and Technicians (17-3) all display intensities above 3%, with the latter two also showing large absolute numbers of low-carbon vacancies. The corresponding distribution of broad-skill shares within these groups is reported in Appendix Table F.5.

Table C.1: Share of high-carbon ads by SOC minor group (3-digits), weighted by BLS employment

SOC minor group	High carbon ads	Share within occupation
17-2 - Engineers	111,600	4.1%
47-1 - Supervisors of Construction and Extraction Workers	4,077	3.4%
47-2 - Construction Trades Workers	14,478	0.8%
47-3 - Helpers, Construction Trades	82	0.1%
47-4 - Other Construction and Related Workers	4,234	2.2%
47-5 - Extraction Workers	101,215	100.0%
Total	235,686	0.3%

Notes: This table shows the number and share of high-carbon ads by 3-digit SOC group, from 2010 to 2019, weighted by BLS employment. *Source:* BLS and Lightcast.

We follow the standard SOC classification in defining high- and low-skilled occupations: major groups 11-29 are classified as high-skilled, while major groups 31-53 are classified as low-skilled. See Appendix D for the full list.

Table C.2: Low-carbon ads and weighted shares by 2-digit SOC group

SOC major group	Low carbon ads	Share within occupation
47 - Construction and Extraction	119,317	4.4%
17 - Architecture and Engineering	279,902	4.1%
19 - Life, Physical, and Social Science	53,152	3.3%
49 - Installation, Maintenance, and Repair	208,420	2.6%
13 - Business and Financial Operations	109,839	1.6%
45 - Farming, Fishing, and Forestry	1,389	1.3%
11 - Management	295,183	1.3%
51 - Production	60,383	1.0%
53 - Transportation and Material Moving	61,903	1.0%
33 - Protective Service	17,763	0.8%
23 - Legal	10,536	0.6%
15 - Computer and Mathematical	144,742	0.6%
27 - Arts, Design, Entertainment, Sports, and Media	21,746	0.4%
41 - Sales and Related	154,203	0.4%
37 - Building and Grounds Cleaning and Maintenance	12,362	0.4%
43 - Office and Administrative Support	97,811	0.4%
21 - Community and Social Service	4,423	0.3%
25 - Education, Training, and Library	18,970	0.2%
39 - Personal Care and Service	7,078	0.2%
29 - Healthcare Practitioners and Technical	35,582	0.1%
35 - Food Preparation and Serving Related	9,618	0.1%
31 - Healthcare Support	7,433	0.1%
Total	1,731,755	0.9%

Notes: This table shows the number and weighted (by BLS employment) shares of low-carbon jobs by 2-digit SOC group, from 2010 to 2019. The occupations are ranked by the shares, separately for high-skilled and low-skilled groups.

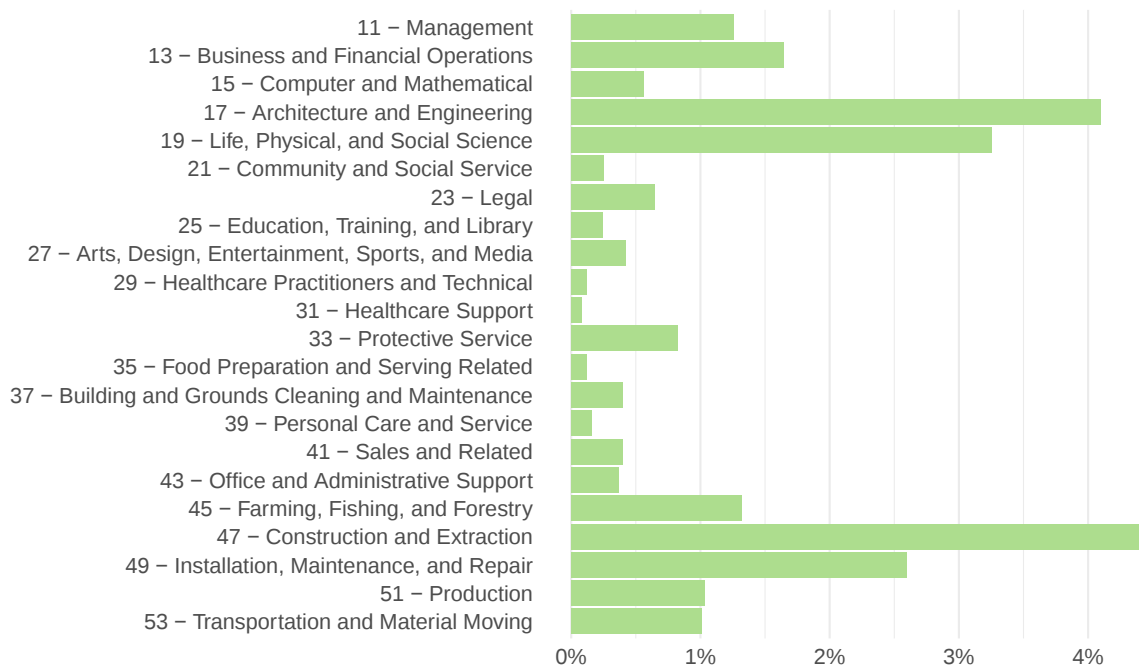


Figure C.1: Low-carbon ads intensity by occupation (2010-2019)

Table C.3: Share of low-carbon ads by SOC minor group (3-digits), weighted by BLS employment

SOC minor group	Low carbon ads	Share within occupation
13-1 - Business Operations Specialists	89,424	2.4%
13-2 - Financial Specialists	20,415	0.4%
17-1 - Architects, Surveyors, and Cartographers	11,967	4.2%
17-2 - Engineers	213,423	4.3%
17-3 - Engineering and Mapping Technicians	54,512	3.6%
19-1 - Life Scientists	10,584	2.0%
19-2 - Physical Scientists	21,053	7.3%
19-3 - Social Scientists and Related Workers	8,422	2.0%
19-4 - Life, Physical, and Social Science Technicians	13,093	2.0%
Total	1,731,755	0.9%

Table C.4: Share of low-carbon ads by NAICS sector (unweighted averages, 2010-2019)

NAICS2	Ad count			Unweighted ad share		
	Generic	Low carbon	High carbon	Generic	Low carbon	High carbon
11 - "Agriculture, Forestry, Fishing and Hunting"	130,495	2,741	186	97.8%	2.1%	0.1%
21 - "Mining, Quarrying, and Oil and Gas Extraction"	554,701	9,139	80,732	86.1%	1.4%	12.5%
22 - Utilities	594,468	78,818	8,816	87.2%	11.6%	1.3%
23 - Construction	1,998,827	79,385	4,358	96.0%	3.8%	0.2%
311 - Food Manufacturing	673,389	7,840	132	98.8%	1.2%	0.0%
312 - Beverage and Tobacco Product Manufacturing	384,732	2,559	1,411	99.0%	0.7%	0.4%
313 - Textile Mills	731	6	0	99.2%	0.8%	0.0%
314 - Textile Product Mills	52,939	547	21	98.9%	1.0%	0.0%
315 - Apparel Manufacturing	83,465	63	2	99.9%	0.1%	0.0%
316 - Leather and Allied Product Manufacturing	5,976	6	0	99.9%	0.1%	0.0%
321 - Wood Product Manufacturing	110,355	5,245	425	95.1%	4.5%	0.4%
322 - Paper Manufacturing	103,124	875	84	99.1%	0.8%	0.1%
323 - Printing and Related Support Activities	105,554	282	80	99.7%	0.3%	0.1%
324 - Petroleum and Coal Products Manufacturing	122,196	5,449	23,841	80.7%	3.6%	15.7%
325 - Chemical Manufacturing	1,975,635	17,131	1,258	99.1%	0.9%	0.1%
326 - Plastics and Rubber Products Manufacturing	78,987	722	7	99.1%	0.9%	0.0%
327 - Nonmetallic Mineral Product Manufacturing	210,998	4,606	1,225	97.3%	2.1%	0.6%
331 - Primary Metal Manufacturing	149,109	2,058	820	98.1%	1.4%	0.5%
332 - Fabricated Metal Product Manufacturing	284,661	2,231	167	99.2%	0.8%	0.1%
333 - Machinery Manufacturing	923,673	19,650	540	97.9%	2.1%	0.1%
334 - Computer and Electronic Product Manufacturing	1,937,570	25,997	877	98.6%	1.3%	0.0%
335 - "Electrical Equipment, Appliance, and Component Manufacturing"	171,811	6,332	84	96.4%	3.6%	0.0%
336 - Transportation Equipment Manufacturing	1,715,792	31,410	954	98.1%	1.8%	0.1%
337 - Furniture and Related Product Manufacturing	97,321	3,800	90	96.2%	3.8%	0.1%
339 - Miscellaneous Manufacturing	498,216	2,293	58	99.5%	0.5%	0.0%
42 - Wholesale Trade	1,587,068	20,628	1,083	98.7%	1.3%	0.1%
441 - Motor Vehicle and Parts Dealers	1,507,096	9,367	34	99.4%	0.6%	0.0%
442 - Furniture and Home Furnishings Stores	442,550	357	72	99.9%	0.1%	0.0%
443 - Electronics and Appliance Stores	761,021	446	17	99.9%	0.1%	0.0%
444 - Building Material and Garden Equipment and Supplies Dealers	2,008,522	5,953	14	99.7%	0.3%	0.0%
445 - Food and Beverage Stores	1,911,413	3,497	159	99.8%	0.2%	0.0%
446 - Health and Personal Care Stores	1,568,805	852	30	99.9%	0.1%	0.0%
447 - Gasoline Stations	452,843	472	1,058	99.7%	0.1%	0.2%
448 - Clothing and Clothing Accessories Stores	2,089,809	1,286	92	99.9%	0.1%	0.0%
451 - "Sporting Goods, Hobby, Book, and Music Stores"	1,089,087	6,611	73	99.4%	0.6%	0.0%
452 - General Merchandise Stores	4,684,056	3,180	633	99.9%	0.1%	0.0%
453 - Miscellaneous Store Retailers	1,152,443	6,438	128	99.4%	0.6%	0.0%
454 - Nonstore Retailers	553,924	4,404	253	99.2%	0.8%	0.0%
481 - Air Transportation	325,821	1,554	49	99.5%	0.5%	0.0%
482 - Rail Transportation	79,758	12,016	490	86.4%	13.0%	0.5%
483 - Water Transportation	51,745	486	40	99.0%	0.9%	0.1%
484 - Truck Transportation	1,987,524	11,890	553	99.4%	0.6%	0.0%
485 - Transit and Ground Passenger Transportation	216,968	8,712	70	96.1%	3.9%	0.0%
486 - Pipeline Transportation	57,010	2,308	8,661	83.9%	3.4%	12.7%
487 - Scenic and Sightseeing Transportation	923	8	0	99.1%	0.9%	0.0%
488 - Support Activities for Transportation	231,983	1,784	347	99.1%	0.8%	0.1%
491 - Postal Service	100,474	355	1	99.6%	0.4%	0.0%
492 - Couriers and Messengers	505,647	44,404	44	91.9%	8.1%	0.0%
493 - Warehousing and Storage	90,975	566	30	99.3%	0.6%	0.0%
51 - Information	6,017,082	33,920	10,443	99.3%	0.6%	0.2%
52 - Finance and Insurance	14,480,011	29,933	1,967	99.8%	0.2%	0.0%
53 - Real Estate and Rental and Leasing	2,944,807	20,735	674	99.3%	0.7%	0.0%
54 - "Professional, Scientific, and Technical Services"	14,800,810	179,189	15,435	98.7%	1.2%	0.1%
55 - Management of Companies and Enterprises	253,423	2,259	96	99.1%	0.9%	0.0%
56 - Administrative and Support and Waste Management and Remediation Services	8,384,872	78,714	3,758	99.0%	0.9%	0.0%
61 - Educational Services	8,810,942	60,284	622	99.3%	0.7%	0.0%
62 - Health Care and Social Assistance	25,549,338	34,045	6,431	99.8%	0.1%	0.0%
71 - "Arts, Entertainment, and Recreation"	1,276,173	6,704	261	99.5%	0.5%	0.0%
72 - Accommodation and Food Services	10,112,974	53,399	1,543	99.5%	0.5%	0.0%
81 - Other Services (except Public Administration)	2,780,061	35,831	679	98.7%	1.3%	0.0%
92 - Public Administration	5,018,504	86,727	3,406	98.2%	1.7%	0.1%

Appendix D High- and low-skilled occupation

High skilled occupations

- 11 - Management Occupations
 - 13 - Business and Financial Operations Occupations
 - 15 - Computer and Mathematical Occupations
 - 17 - Architecture and Engineering Occupations
 - 19 - Life, Physical, and Social Science Occupations
 - 21 - Community and Social Service Occupations
 - 23 - Legal Occupations
 - 25 - Educational Instruction and Library Occupations
 - 27 - Arts, Design, Entertainment, Sports, and Media Occupations
 - 29 - Healthcare Practitioners and Technical Occupations
-

Low skilled occupations

- 31 - Healthcare Support Occupations
 - 33 - Protective Service Occupations
 - 35 - Food Preparation and Serving Related Occupations
 - 37 - Building and Grounds Cleaning and Maintenance Occupations
 - 39 - Personal Care and Service Occupations
 - 41 - Sales and Related Occupations
 - 43 - Office and Administrative Support Occupations
 - 45 - Farming, Fishing, and Forestry Occupations
 - 47 - Construction and Extraction Occupations
 - 49 - Installation, Maintenance, and Repair Occupations
 - 51 - Production Occupations
 - 53 - Transportation and Material Moving Occupations
-

Appendix E Evolution of low-carbon job shares

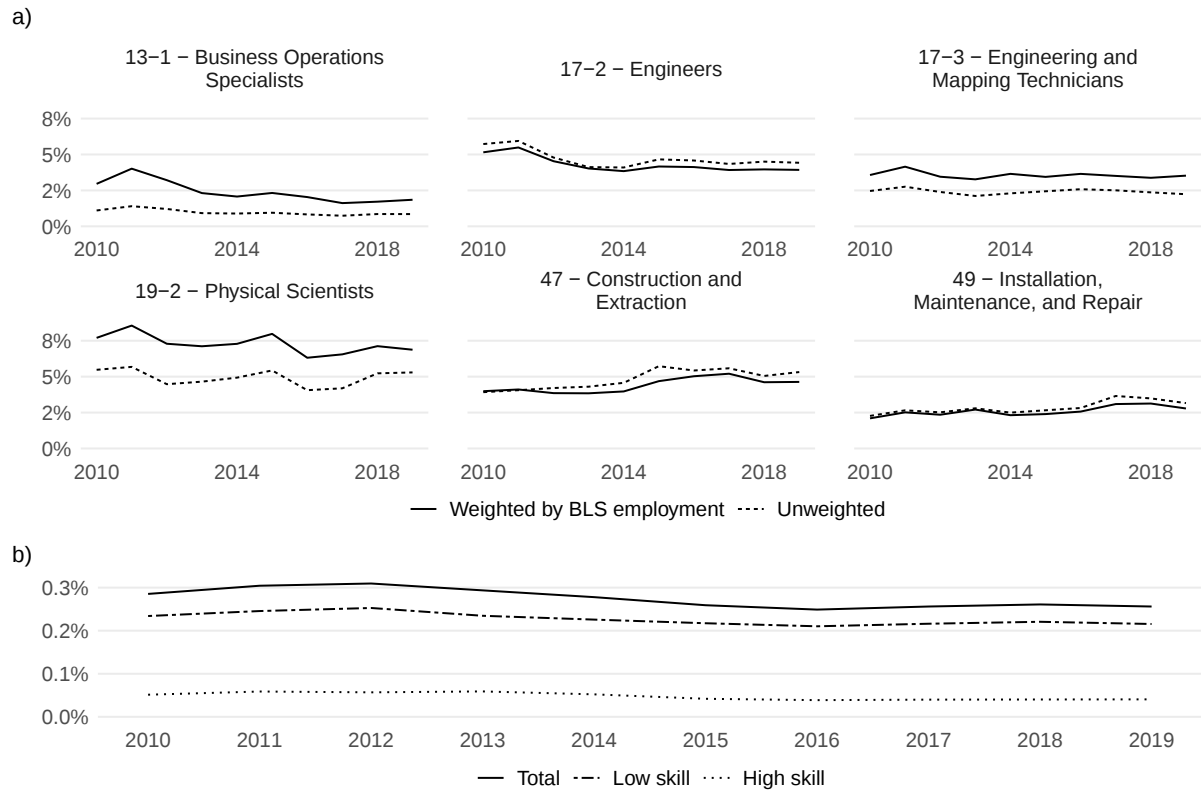


Figure E.1: Evolution of low-carbon (a) and high-carbon (b) vacancy shares in the U.S. by occupation (2010-2019)

Notes: Panel a): Plotted shares of low-carbon ads are first calculated at the 6-digit SOC occupation level as the ratio between the number of low-carbon ads and the total ads within a 6-digit occupation, then averaged for each reported SOC grouping weighing by 6-digit employment obtained from the BLS. Panel b): the same methodology is applied using the definition of high-carbon ads described in Table B.10. *Source:* Lightcast and BLS.

Table E.1: Share of low-carbon ads by year, weighted by BLS employment (2010-2019)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Overall										
All	0.83%	0.97%	0.94%	0.80%	0.81%	0.87%	0.85%	0.86%	0.87%	0.87%
Overall - High skill										
All	0.33%	0.39%	0.34%	0.29%	0.29%	0.29%	0.28%	0.26%	0.26%	0.27%
13-1 - Business Operations Specialists	0.09%	0.13%	0.10%	0.07%	0.07%	0.07%	0.06%	0.05%	0.05%	0.06%
17-2 - Engineers	0.06%	0.06%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%
17-3 - Engineering and Mapping Technicians	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
Others	0.16%	0.18%	0.17%	0.15%	0.16%	0.15%	0.14%	0.14%	0.14%	0.15%
Overall - Low skill										
All	0.50%	0.58%	0.59%	0.52%	0.52%	0.58%	0.58%	0.61%	0.60%	0.60%
47 - Construction and Extraction	0.16%	0.16%	0.15%	0.15%	0.16%	0.18%	0.20%	0.20%	0.18%	0.18%
49 - Installation, Maintenance, and Repair	0.08%	0.10%	0.09%	0.11%	0.09%	0.09%	0.10%	0.12%	0.12%	0.11%
53	0.07%	0.07%	0.09%	0.06%	0.06%	0.07%	0.07%	0.07%	0.07%	0.07%
Within occupation group										
Others	0.19%	0.25%	0.26%	0.20%	0.21%	0.23%	0.21%	0.22%	0.23%	0.24%
13-1 - Business Operations Specialists	2.96%	4.01%	3.21%	2.31%	2.07%	2.32%	2.04%	1.62%	1.71%	1.85%
17-2 - Engineers	5.15%	5.49%	4.53%	4.03%	3.84%	4.16%	4.12%	3.92%	3.96%	3.93%
17-3 - Engineering and Mapping Technicians	3.57%	4.15%	3.45%	3.27%	3.65%	3.44%	3.65%	3.51%	3.38%	3.53%
19-2 - Physical Scientists	7.70%	8.56%	7.29%	7.11%	7.28%	7.98%	6.31%	6.55%	7.12%	6.87%
47 - Construction and Extraction	3.99%	4.11%	3.85%	3.84%	3.97%	4.69%	5.03%	5.20%	4.61%	4.63%
49 - Installation, Maintenance, and Repair	2.10%	2.51%	2.35%	2.71%	2.32%	2.39%	2.57%	3.09%	3.13%	2.78%

Notes: Table E.1 presents the annual share low-carbon ads for each of the SOC occupational groups harboring the most low-carbon positions. low-carbon shares are calculated at the SOC 6-digit level then weighted using mean employment by 6-digits occupation for the period 2010-2019 obtained from the BLS Occupational Employment and Wage Statistics.

Appendix F Skill gap

Table F.1: Keywords defining broad skills

Broad skill	Keywords	Lightcast skills
Cognitive	problem solving, research, analytical, critical thinking, math, statistics	123
IT	<i>Burning Glass Technologies Information Technology skill cluster family</i>	1,588
Management	project management, system analysis, system evaluat*, updat* kno*, using know*, consultation* advice*, supervisory, leadership, management, mentoring, staff	484
Social	communication, teamwork, collaboration, negotiation, presentation	78
Technical	engineer*, technolog*, design, build*, construct*, mechanic*, draft, lay* out, specify* techn* part*, specify* techn* devic*, specify*, techn* equip*, estimat* quant* character*, technic*	133

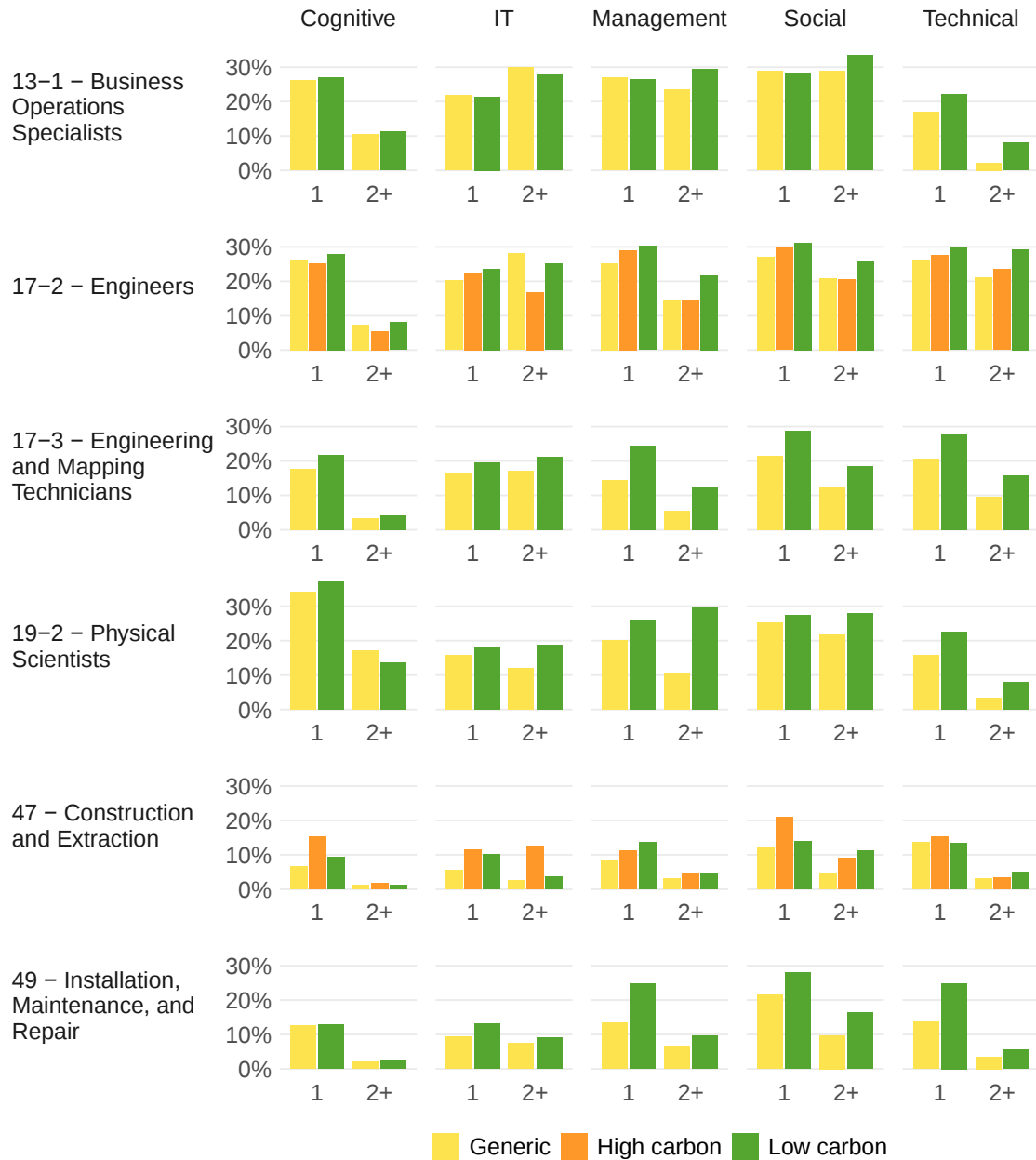


Figure F.1: Differences in broad skills by occupation

Notes: Each panel represents an occupation (vertical) and a broad skill category (horizontal). For each job type (generic, low- or high-carbon), each panel shows the share of job ads that contains *exactly one* or *two or more* (2+, intensive margin) skills in that broad skill category. Percentages reported correspond to unweighted shares of ads obtained directly from the sample, as these refer to within-occupation shares. See text for full description including how the five broad skill categories are defined.

Table F.2: Skill gap

	Cognitive		IT		Management		Social		Technical	
	1	2+	1	2+	1	2+	1	2+	1	2+
13-1 - Business Operations Specialists										
Generic	26.1%	10.4%	21.9%	29.9%	26.9%	23.4%	28.8%	28.9%	16.9%	2.2%
Low carbon	26.9%	11.3%	21.4%	27.7%	26.5%	29.3%	28.1%	33.5%	22.0%	8.0%
17-2 - Engineers										
Generic	26.3%	7.4%	20.3%	28.1%	25.2%	14.5%	27.1%	20.9%	26.2%	21.0%
High carbon	25.2%	5.6%	22.2%	16.9%	29.0%	14.5%	30.0%	20.7%	27.6%	23.5%
Low carbon	28.0%	8.0%	23.6%	25.1%	30.2%	21.8%	31.2%	25.8%	29.7%	29.3%
17-3 - Engineering and Mapping Technicians										
Generic	17.7%	3.3%	16.3%	17.1%	14.3%	5.6%	21.5%	12.4%	20.6%	9.6%
Low carbon	21.7%	4.2%	19.7%	21.1%	24.4%	12.4%	28.7%	18.5%	27.7%	15.8%
19-2 - Physical Scientists										
Generic	34.2%	17.3%	15.9%	12.0%	20.3%	10.6%	25.3%	21.9%	15.9%	3.4%
Low carbon	37.2%	13.5%	18.4%	18.7%	26.1%	29.8%	27.3%	28.1%	22.6%	7.9%
47 - Construction and Extraction										
Generic	6.7%	1.2%	5.5%	2.6%	8.6%	3.2%	12.2%	4.5%	13.5%	3.2%
High carbon	15.3%	1.8%	11.6%	12.6%	11.2%	4.7%	20.9%	9.1%	15.1%	3.4%
Low carbon	9.4%	1.1%	10.2%	3.7%	13.8%	4.4%	13.9%	11.2%	13.5%	5.1%
49 - Installation, Maintenance, and Repair										
Generic	12.7%	1.9%	9.4%	7.5%	13.4%	6.6%	21.5%	9.8%	13.8%	3.5%
Low carbon	12.8%	2.3%	13.2%	9.0%	24.8%	9.6%	28.0%	16.4%	24.9%	5.7%

Notes: Within each occupation and ad category (generic or low-carbon), the value listed reports the unweighted sample share of ads containing exactly one, or 2 or more skills in each of the five broad skill categories. E.g. 25.2% of generic Business and Operations Specialists ads require exactly one Cognitive skill.

Table F.3: Skill gap magnitude across commuting zones

i. Extensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	0.90%	-0.30%	-0.30%	-0.60%	5.30% ***
17-2 - Engineers	1.70% ***	3.40% ***	5.00% ***	4.20% ***	3.40% ***
17-3 - Engineering and Mapping Technicians	4.50% ***	4.10% ***	10.80% ***	7.50% ***	7.50% ***
19-2 - Physical Scientists	3.60% ***	2.90% ***	6.40% ***	2.60% ***	7.20% ***
47 - Construction and Extraction	3.00% ***	5.10% ***	5.50% ***	2.00% ***	0.10%
49 - Installation, Maintenance, and Repair	0.20%	3.80% ***	11.50% ***	6.70% ***	11.20% ***
b) High carbon vs Generic ads					
17-2 - Engineers	-1.00%	2.10% ***	3.90% ***	3.10% ***	1.50% **
47 - Construction and Extraction	9.00% ***	6.40% ***	2.80% ***	8.90% ***	1.90% ***
c) Low carbon vs High carbon ads					
17-2 - Engineers	2.70% **	1.30% **	1.10% *	1.10%	1.90% **
47 - Construction and Extraction	-5.90% ***	-1.30% **	2.70% ***	-7.00% ***	-1.70% ***

ii. Intensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	1.30% *	-2.10% ***	6.10% ***	4.80% ***	6.00% ***
17-2 - Engineers	0.70% **	-2.90% ***	7.30% ***	5.00% ***	8.30% ***
17-3 - Engineering and Mapping Technicians	1.70% ***	4.60% ***	7.30% ***	6.90% ***	7.00% ***
19-2 - Physical Scientists	-2.80% ***	7.30% ***	19.60% ***	6.90% ***	5.30% ***
47 - Construction and Extraction	0.10%	1.50% ***	1.60% ***	7.30% ***	2.10% ***
49 - Installation, Maintenance, and Repair	0.50% ***	1.60% ***	3.10% ***	6.90% ***	2.30% ***
b) High carbon vs Generic ads					
17-2 - Engineers	-1.60% ***	-11.00% ***	0.20%	-0.10%	2.80% **
47 - Construction and Extraction	0.80% ***	10.30% ***	1.70% ***	4.90% ***	0.40% **
c) Low carbon vs High carbon ads					
17-2 - Engineers	2.30% ***	8.10% ***	7.10% ***	5.10% ***	5.50% ***
47 - Construction and Extraction	-0.70% ***	-8.80% ***	-0.20%	2.40% ***	1.70% ***

Notes: Similar to Table F.2, we compute for each occupation and ad category (generic, low- or high-carbon), the unweighted share of ads containing exactly one (extensive margin), or 2 or more skills (intensive margin) in each of the five broad skill categories. We repeat this calculation in each commuting zone as defined in section 6. We then use the resulting distribution to test the statistical significance of the skill gap magnitude between each ad category pair. Panel a) reports the difference between low-carbon and generic ads in each occupation. A positive (resp. negative) value indicates that low-carbon ads require the particular broad skill considered more (resp. less) frequently. *E.g.* the share of low-carbon Engineers ads requiring exactly one technical skill is 4.2% higher than their generic counterparts, while the share requiring two or more technical skills is 8.3% higher. Stars indicate the statistical significance of this difference, with three stars correspond to the 1% threshold. Similarly, Panel b) compares the skill intensity of high-carbon and generic ads (a positive value indicates that high-carbon ads require more of the skill considered), and Panel c) compares the skill intensity of low and high-carbon ads (a positive value indicates that low-carbon ads require more of the skill considered).

Table F.4: Within-firm differences in skill vector length (winsorized at 30 skills per ad) between low carbon and generic ads

	13-1 - Business Operations Specialists	17-2 - Engineers	17-3 - Engineering and Mapping Technicians
Low carbon	1.243*** (0.137)	2.452*** (0.147)	2.774*** (0.222)
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
R^2	0.31	0.27	0.41
Observations	6,549,642	2,957,995	1,397,391

	19-2 - Physical Scientists	47 - Construction and Extraction	49 - Installation, Maintenance, and Repair
Low carbon	2.158*** (0.192)	2.599*** (0.232)	2.501*** (0.420)
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
R^2	0.42	0.53	0.47
Observations	284,835	1,235,908	5,017,358

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the skill vector length, which is regressed on a binary variable indicating whether a job ad is low carbon or not, and on firm fixed effects. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

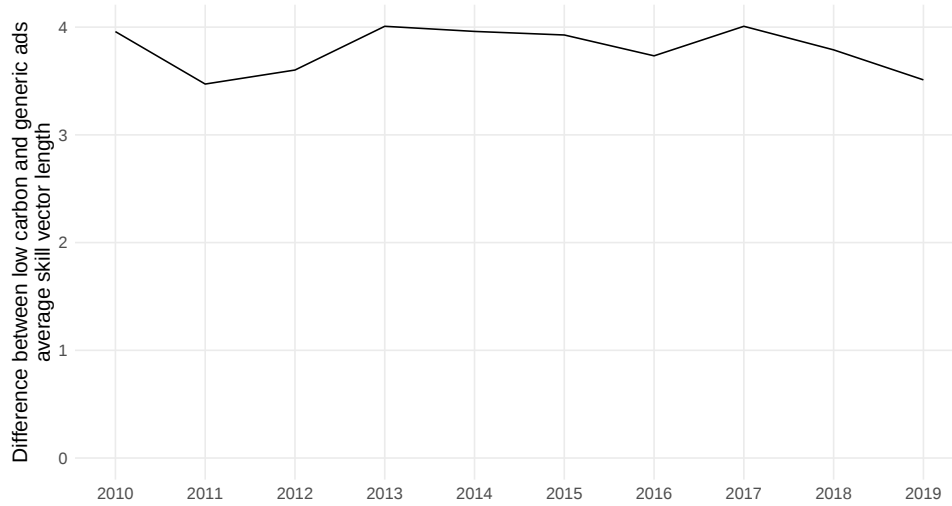


Figure F.2: Average skill vector length in generic and low carbon ads (2010-2019)

Notes: Difference in the unconditional mean of the number of skills low carbon ads and generic ads in our six focus occupations.

Table F.5: Share of ads containing a specific broad skill, by occupation

	Cognitive	IT	Management	Social	Technical
13-1 - Business Operations Specialists	36.5%	51.8%	50.4%	57.7%	19.2%
17-2 - Engineers	33.8%	48.2%	40.5%	48.5%	48.0%
17-3 - Engineering and Mapping Technicians	21.1%	33.5%	20.4%	34.2%	30.5%
19-2 - Physical Scientists	51.4%	28.4%	32.1%	47.6%	19.8%
47 - Construction and Extraction	8.5%	9.3%	12.4%	17.8%	17.0%
49 - Installation, Maintenance, and Repair	14.6%	17.1%	20.4%	31.6%	17.7%
All occupations	23.3%	30.7%	34.1%	42.6%	14.4%

F.1 Reskilling paths indicator

We introduce a new synthetic index that measures the divergent reskilling paths across occupational groups. This index is derived from correlating two measures of skill importance that are constructed as Balassa indexes of revealed comparative advantage, varying between -1 and 1. It can be widely applied to similar datasets and is particularly useful for high-dimensional data like the skill vector in job vacancy data. It is in a similar vein as [Alabdulkareem et al. \(2018\)](#) that use Balassa index to summarize O*NET data constructing a measure of skill complementarity.

The first index termed “low-carbon skill coreness” (C_{sk}^i) assesses the importance of a skill s in a low-carbon ($i = g$) occupation k relative to generic ads within the same occupation. Similarly, a high-carbon skill coreness indicator assesses the importance in high-carbon ads ($i = hc$). The second index termed “skill coreness” (G_{sk}), assesses the importance of a skill s within a particular occupation relative to all other occupations. Maintaining the notations of previous section, we define the two indexes as:

$C_{sk}^i = \frac{f_{sk}^i/f_{sk}-1}{f_{sk}^i/f_{sk}+1}$ and $G_{sk} = \frac{f_{sk}/f_s-1}{f_{sk}/f_s+1}$; where f_{sk}^i are defined as above. A positive value of C_{sk}^i indicates that coreness of skill s in low-(or high-) carbon jobs within SOC k is greater than its coreness across all jobs within that SOC, indicating higher demand from low- (or high-) carbon jobs within that SOC. Similarly, a positive value of G_{sk} indicates greater demand for skill s within SOC j compared to its demand across all occupations.

The correlation coefficient between the two captures green reskilling paths: $Reskilling_k^g = corr_s(C_{sk}^g, G_{sk})$. This is obtained from a regression weighted by the share of each skill in generic ads. If $corr_s(C_{sk}^g, G_{sk}) > 0$, the skills required for low-carbon jobs in occupation j belong to the core set of skills demanded by that occupation, indicating that a transition to low-carbon jobs will require workers to further specialize in their main area of work. Conversely, if $corr_s(C_{sk}^g, G_{sk}) < 0$, the skills required for low-carbon jobs in occupation j are outside of the core skill set required by that occupation. Therefore, workers seeking

green jobs must diversify their skill sets and acquire new skills the usual occupational profile.

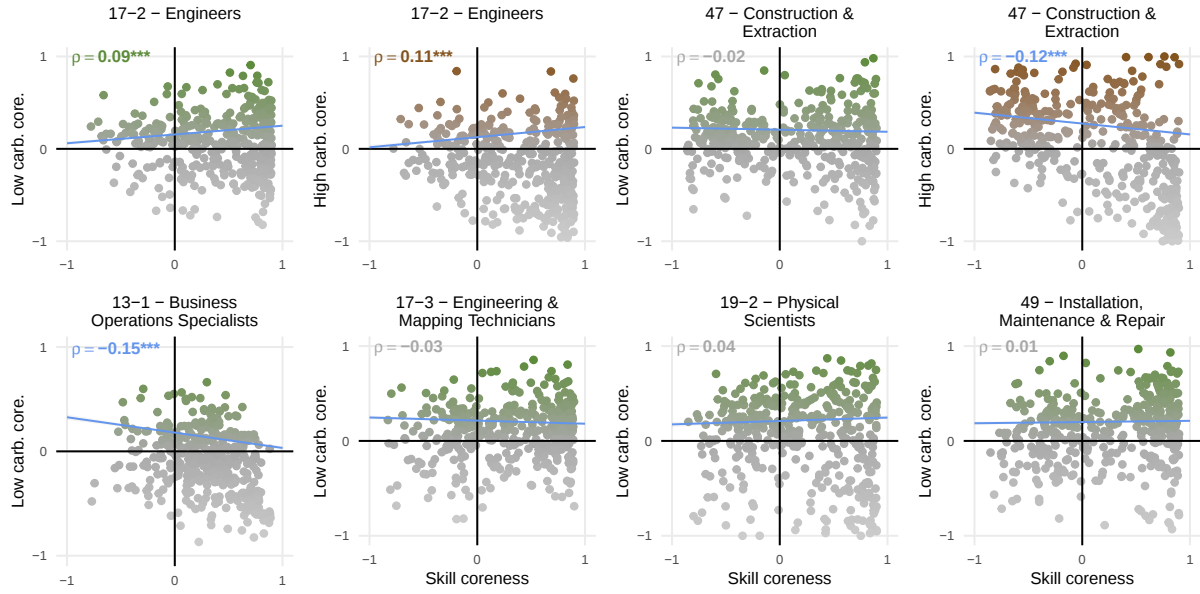


Figure F.3: Specialization vs diversification by occupation excluding highly specific skills (excluding $C_{sk}^g > 0.9$)

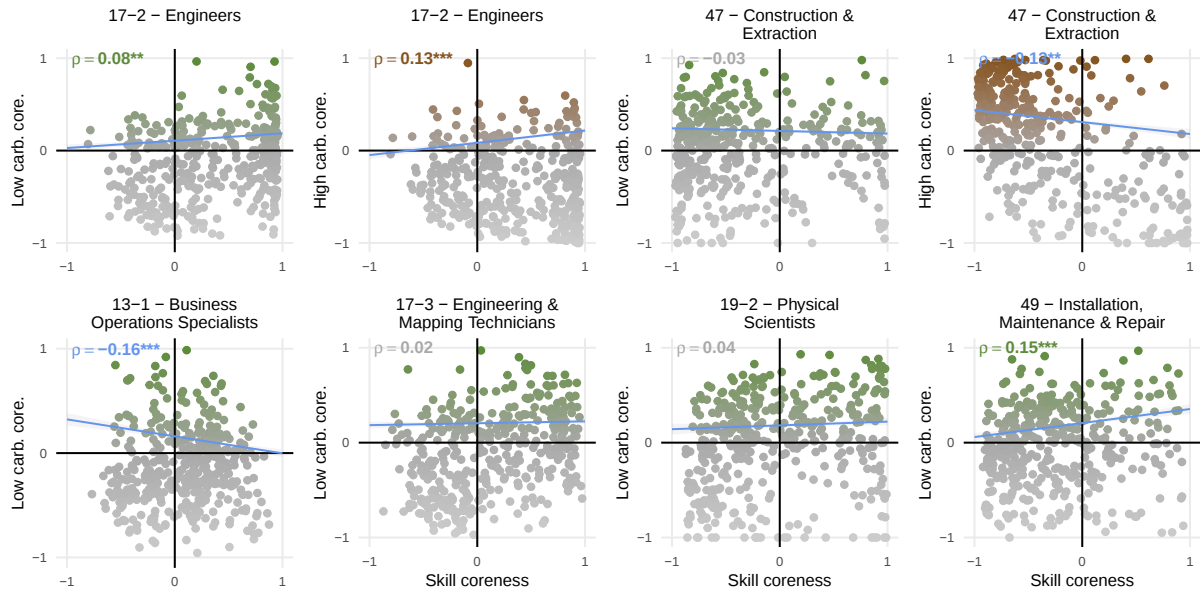


Figure F.4: Specialization vs diversification by occupation, restricted to the five key skills categories

Appendix G Wage regressions robustness

Table G.1: Wage sample balance

	Full sample									
	Ad count	Skills count		Education		Experience		Salary		
		Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	
13-1 - Business Operations Specialists										
Generic	9,536,203	11.5	7.5	13.5	5.4	3.9	2.6	62,241	35,585	
Low carbon	89,329	14.8	8.4	13.8	5.2	4.3	3.0	69,972	36,898	
17-2 - Engineers										
Generic	4,270,532	11.9	7.4	15.0	4.2	5.2	3.1	84,558	36,146	
High carbon	111,600	10.6	6.6	15.5	3.0	6.0	3.5	108,570	58,064	
Low carbon	213,376	16.2	8.4	15.2	3.9	5.3	3.2	85,182	32,731	
17-3 - Engineering and Mapping Technicians										
Generic	2,224,020	9.5	6.8	11.4	5.2	3.7	2.7	48,356	24,900	
Low carbon	54,493	14.5	7.8	12.5	4.6	4.3	2.9	56,624	25,991	
19-2 - Physical Scientists										
Generic	405,443	10.9	6.8	16.0	4.1	4.3	3.2	71,482	42,134	
Low carbon	21,048	15.7	8.5	15.9	4.1	4.3	3.2	68,883	29,015	
47 - Construction and Extraction										
Generic	2,141,068	6.3	5.6	6.8	6.2	3.7	2.5	46,385	25,543	
High carbon	124,080	7.9	6.1	10.7	5.0	3.1	2.6	50,191	28,298	
Low carbon	119,298	10.0	7.2	8.0	6.0	3.3	2.4	49,267	28,201	
49 - Installation, Maintenance, and Repair										
Generic	6,851,868	8.4	6.3	9.4	5.4	3.1	2.3	46,498	25,784	
Low carbon	208,403	13.4	7.4	9.2	5.6	3.1	2.4	52,758	23,895	

	Has wage information											
	Ad count	Skills count			Education			Experience			Salary	
		Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.
13-1 - Business Operations Specialists												
Generic	1,604,383	10.6	7.2	-0.88***	11.9	6.5	-1.54***	3.2	2.3	-0.652***	62,241	35,585
Low carbon	17,767	13.8	8.5	-0.923***	11.5	7.0	-2.27***	3.3	2.6	-0.991***	69,972	36,898
17-2 - Engineers												
Generic	558,875	11.2	7.4	-0.645***	14.5	4.7	-0.441***	4.4	3.0	-0.747***	84,558	36,146
High carbon	7,525	9.4	6.9	-1.18***	14.9	4.2	-0.563***	5.9	3.5	-0.0982**	108,570	58,064
Low carbon	28,701	16.5	9.4	0.226***	14.8	4.4	-0.389***	4.4	3.1	-0.882***	85,182	32,731
17-3 - Engineering and Mapping Technicians												
Generic	482,236	8.6	6.5	-0.862***	10.0	5.9	-1.47***	3.1	2.5	-0.637***	48,356	24,900
Low carbon	9,600	13.8	8.7	-0.766***	11.2	5.5	-1.3***	3.6	2.5	-0.712***	56,624	25,991
19-2 - Physical Scientists												
Generic	73,047	10.7	6.9	-0.268***	15.1	5.0	-0.896***	3.1	2.6	-1.24***	71,482	42,134
Low carbon	6,409	17.0	9.3	1.37***	15.0	5.0	-0.911***	3.1	2.5	-1.23***	68,883	29,015
47 - Construction and Extraction												
Generic	601,438	6.1	5.5	-0.244***	5.4	6.2	-1.39***	3.5	2.4	-0.194***	46,385	25,543
High carbon	15,781	6.5	5.6	-1.33***	8.4	6.1	-2.3***	3.2	2.6	0.124***	50,191	28,298
Low carbon	31,786	9.4	7.6	-0.592***	6.5	6.2	-1.51***	3.1	2.2	-0.193***	49,267	28,201
49 - Installation, Maintenance, and Repair												
Generic	1,329,697	8.0	6.2	-0.42***	7.7	6.0	-1.62***	3.0	2.2	-0.099***	46,498	25,784
Low carbon	36,347	13.0	8.1	-0.387***	8.2	6.0	-0.955***	3.3	2.4	0.158***	52,758	23,895

Has wage, NAICS 2 and degree information												
	Ad count	Skills count			Education			Experience			Salary	
		Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.
13-1 - Business Operations Specialists												
Generic	464,994	12.8	7.6	1.33***	15.3	1.9	1.85***	3.2	2.2	-0.678***	61,644	30,900
Low carbon	5,200	16.9	8.9	2.11***	15.7	2.3	1.91***	3.3	2.4	-0.961***	68,941	30,420
17-2 - Engineers												
Generic	153,384	14.1	8.0	2.23***	16.1	0.7	1.1***	4.1	3.1	-1.04***	87,233	31,952
High carbon	3,609	11.1	7.0	0.458***	16.1	0.6	0.574***	5.9	3.4	-0.102*	105,835	47,063
Low carbon	11,076	19.5	9.4	3.24***	16.1	0.8	0.885***	4.1	3.3	-1.22***	87,906	30,841
17-3 - Engineering and Mapping Technicians												
Generic	96,432	10.8	7.3	1.31***	13.3	1.8	1.83***	3.2	2.4	-0.536***	51,132	24,703
Low carbon	2,918	16.7	10.2	2.19***	13.8	1.9	1.28***	3.7	2.5	-0.581***	58,250	25,020
19-2 - Physical Scientists												
Generic	31,508	12.4	6.8	1.43***	16.7	1.6	0.752***	3.0	2.6	-1.31***	71,872	38,084
Low carbon	2,692	18.1	8.5	2.44***	16.8	1.7	0.894***	2.7	2.3	-1.61***	71,802	26,513
47 - Construction and Extraction												
Generic	76,338	9.1	6.6	2.73***	12.3	1.0	5.44***	3.6	2.3	-0.0535***	48,873	23,562
High carbon	4,253	9.2	6.7	1.35***	12.7	1.5	2.07***	3.0	2.2	-0.0613*	51,808	24,039
Low carbon	5,197	14.4	7.9	4.4***	12.3	1.1	4.31***	3.6	2.4	0.288***	56,717	33,432
49 - Installation, Maintenance, and Repair												
Generic	300,614	9.5	6.8	1.09***	12.3	1.0	2.93***	3.0	2.2	-0.101***	43,580	22,749
Low carbon	8,661	15.8	8.3	2.38***	12.4	1.0	3.24***	3.3	2.3	0.223***	53,257	26,035

	Has wage and firm information											
	Ad count	Skills count			Education			Experience			Salary	
		Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.	t-test	Mean	St. Dev.
13-1 - Business Operations Specialists												
Generic	887,188	11.7	7.4	0.232***	11.5	6.8	-1.91***	3.1	2.4	-0.737***	62,694	33,956
Low carbon	12,692	14.4	8.6	-0.359***	11.2	7.2	-2.63***	3.1	2.5	-1.16***	70,688	35,985
17-2 - Engineers												
Generic	229,663	13.2	8.2	1.3***	14.3	5.2	-0.726***	4.1	3.1	-1.09***	84,882	36,562
High carbon	3,218	11.3	7.8	0.709***	14.3	5.2	-1.23***	5.1	3.5	-0.899***	99,932	57,942
Low carbon	15,491	18.6	9.4	2.34***	14.6	4.6	-0.568***	4.0	3.2	-1.32***	84,358	32,110
17-3 - Engineering and Mapping Technicians												
Generic	227,752	9.9	7.1	0.389***	9.5	6.0	-1.94***	2.9	2.5	-0.781***	49,215	24,811
Low carbon	5,489	15.4	8.5	0.844***	11.1	5.6	-1.4***	3.5	2.5	-0.844***	56,970	25,332
19-2 - Physical Scientists												
Generic	40,457	11.6	7.2	0.653***	15.1	5.3	-0.887***	2.8	2.5	-1.56***	76,640	44,204
Low carbon	4,494	17.3	8.9	1.6***	15.0	5.2	-0.923***	2.8	2.4	-1.54***	71,204	28,655
47 - Construction and Extraction												
Generic	290,818	7.2	5.9	0.811***	5.5	6.1	-1.3***	3.6	2.5	-0.108***	48,980	24,980
High carbon	9,368	7.4	5.9	-0.448***	7.9	6.2	-2.81***	3.2	2.5	0.191***	49,620	23,475
Low carbon	17,606	11.0	7.8	1.01***	6.8	6.2	-1.23***	3.2	2.2	-0.107***	52,538	28,308
49 - Installation, Maintenance, and Repair												
Generic	837,707	8.7	6.4	0.27***	7.4	6.0	-1.91***	2.9	2.2	-0.199***	46,675	25,479
Low carbon	24,911	13.9	8.2	0.494***	7.9	6.0	-1.24***	3.2	2.3	0.0797***	53,535	24,073

Notes: The subtables of Table G.1 provide descriptive statistics for each of the samples used in the specifications of Table 4. The *t*-tests reported are computed against the distribution of the respective variables in the full sample.

Table G.2: Correlation between firm-level share of low-carbon ads and firm-level wage fixed effects

	2010-2012	2017-2019	All years
	(10)	(11)	(12)
Firm-level wage FE	0.006*** (0.001)	0.012*** (0.001)	0.011*** (0.001)
Observations	41,015	277,146	341,803
R^2	0.00042	0.0012	0.001

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Firm FEs are recovered by regressing the log of the offered salary on firm FE, controlling for year, skill vector length, commuting zone and SOC (3-digits) FEs.

Table G.3: Relationship between low-carbon job and wage offer (job ad length winsorized at 30 skills)

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.079*** (0.010)	0.052*** (0.010)	0.045*** (0.005)	0.030*** (0.004)	0.065*** (0.005)	0.037*** (0.004)
Observations	759,507	273,544	2,418,122	1,600,343	4,748,666	2,578,408
R^2	0.27	0.74	0.23	0.69	0.24	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The specifications of Table 4 are estimated on the initial and final periods of our sample, while winsorizing the skill vector length to a maximum of 30 skills per ad. Standard errors are clustered at the Commuting Zone level.

Table G.4: Relationship between low-carbon job and wage offer (consistent sample)

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.064*** (0.013)	0.052*** (0.010)	0.054*** (0.006)	0.030*** (0.004)	0.071*** (0.006)	0.037*** (0.004)
Observations	273,544	273,544	1,600,343	1,600,343	2,578,408	2,578,408
R^2	0.28	0.74	0.23	0.69	0.24	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table G.5: Relationship between low-carbon job and wage offer (no SOC-3 FEs)

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.079*** (0.011)	0.052*** (0.011)	0.025*** (0.007)	0.015*** (0.005)	0.050*** (0.006)	0.028*** (0.005)
Observations	759,507	273,544	2,418,122	1,600,343	4,748,666	2,578,408
R^2	0.13	0.71	0.1	0.66	0.12	0.63
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The specifications of Table 4 are estimated on the initial and final periods of our sample, while excluding 3-digits SOC occupational code from our FE structure. Standard errors are clustered at the Commuting Zone level.

Table G.6: Relationship between low-carbon job and wage offer (with industry and education FEs)

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.053*** (0.013)	0.036*** (0.012)	0.036*** (0.008)	0.037*** (0.007)	0.071*** (0.008)	0.035*** (0.007)
Observations	182,897	105,689	593,068	490,882	1,154,316	876,865
R^2	0.42	0.74	0.4	0.69	0.39	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS (2-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The specifications of Table 4 are estimated on the initial and final periods of our sample, while including 2-digit NAICS industry codes and educational requirements in our FE structure. Standard errors are clustered at the Commuting Zone level.

Table G.7: Relationship between low-carbon job and wage offer (unweighted)

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Job is low carbon	0.058*** (0.009)	0.040*** (0.007)	0.031*** (0.004)	0.022*** (0.003)	0.043*** (0.004)	0.029*** (0.004)
Observations	759,507	273,544	2,418,122	1,600,343	4,748,666	2,578,408
R^2	0.27	0.73	0.24	0.66	0.25	0.64
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The specifications of Table 4 are estimated on the initial and final periods of our sample, without weighting for BLS employment. Standard errors are clustered at the Commuting Zone level.

Table G.8: Low-carbon job and wage offer relationship by occupation

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
13-1 - Business Operations Specialists						
Job is low carbon	0.112*** (0.021)	0.073*** (0.015)	0.101*** (0.017)	0.032*** (0.009)	0.09*** (0.013)	0.032*** (0.007)
Observations	232,507	90,355	868,497	576,455	1,602,229	888,176
Low carbon ads	2,869	1,399	9,061	7,392	17,456	12,468
R^2	0.1	0.74	0.08	0.68	0.09	0.64
17-2 - Engineers						
Job is low carbon	0.022* (0.013)	-0.003 (0.011)	-0.035*** (0.009)	0 (0.008)	-0.007 (0.006)	0 (0.006)
Observations	131,354	40,493	239,746	124,776	588,505	246,083
Low carbon ads	7,038	2,540	11,151	7,384	28,867	15,650
R^2	0.13	0.75	0.1	0.62	0.1	0.6
17-3 - Engineering and Mapping Technicians						
Job is low carbon	0.14*** (0.014)	0.083*** (0.024)	0.064*** (0.009)	0.006 (0.013)	0.076*** (0.01)	0.02* (0.01)
Observations	80,346	24,325	240,209	139,460	486,473	230,563
Low carbon ads	1,695	626	4,607	3,035	9,474	5,399
R^2	0.15	0.79	0.12	0.7	0.12	0.66
19-2 - Physical Scientists						
Job is low carbon	0.005 (0.028)	0.002 (0.023)	-0.047** (0.019)	-0.002 (0.011)	-0.03** (0.014)	0.004 (0.008)
Observations	16,794	7,966	31,480	19,675	77,550	44,168
Low carbon ads	980	625	2,717	1,926	6,274	4,380
R^2	0.23	0.84	0.2	0.74	0.16	0.73
47 - Construction and Extraction						
Job is low carbon	0.037* (0.019)	0.012 (0.022)	-0.016 (0.01)	-0.019 (0.012)	0.006 (0.009)	0.013 (0.01)
Observations	92,652	25,341	334,835	207,864	642,275	314,734
Low carbon ads	3,746	1,296	16,598	11,105	31,917	17,632
R^2	0.17	0.76	0.16	0.74	0.18	0.7
49 - Installation, Maintenance, and Repair						
Job is low carbon	0.085*** (0.015)	0.059*** (0.016)	0.056*** (0.006)	0.052*** (0.007)	0.091*** (0.007)	0.056*** (0.006)
Observations	205,854	85,064	703,355	532,113	1,351,634	854,684
Low carbon ads	5,356	2,408	18,114	14,220	36,026	24,702
R^2	0.13	0.73	0.12	0.69	0.13	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

Notes: We estimate the specifications of Table 4 on each of our six main SOC groups of interest by splitting the sample. Standard errors are clustered at the CZ level.

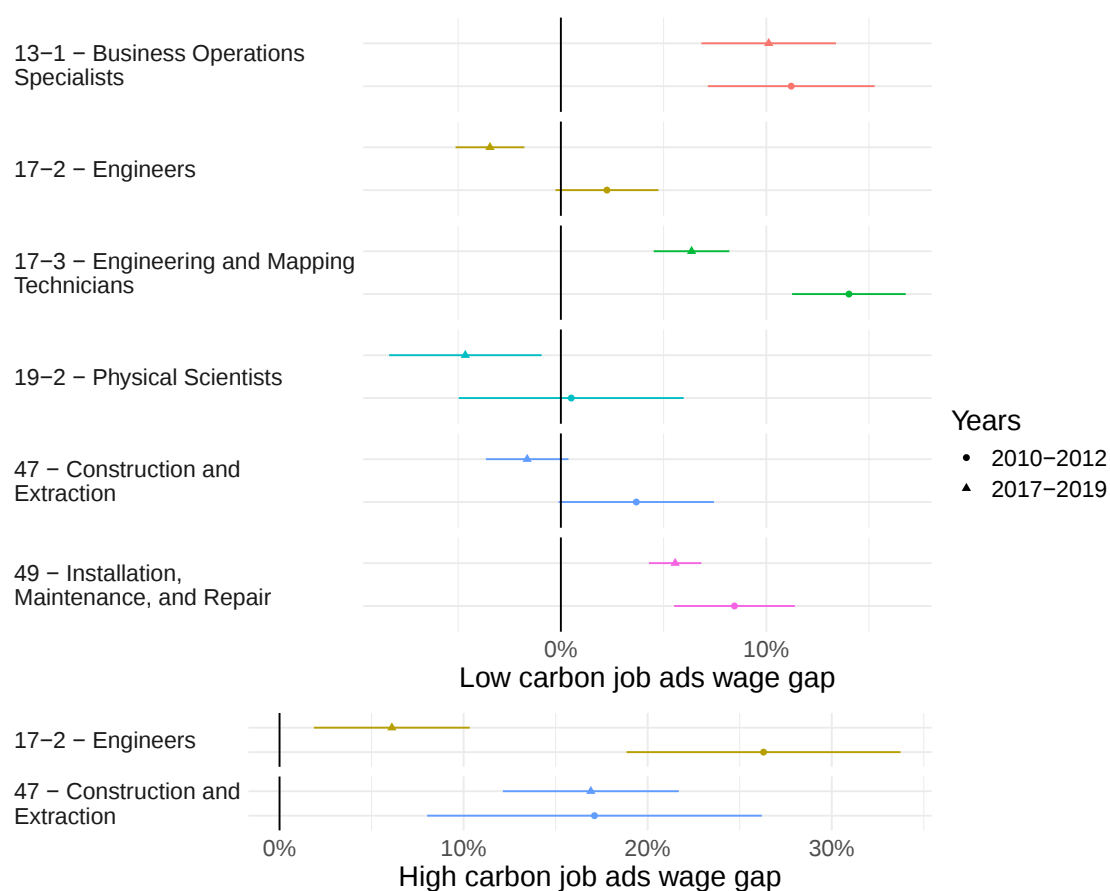


Figure G.1: Wage gap between generic jobs ads and low-/ high-carbon job ads by SOC group and period

Notes: In the top panel, we estimate specification (1) of Table 4 on each of our six main SOC groups of interest over the periods 2010-2012 and 2017-2019 by splitting the sample. In the bottom panel, we then complement these six estimates with an application of specification (1) to the high-carbon wage gap estimation. Error bars indicate 95% confidence intervals.

Table G.9: Relationship between high-carbon job and wage offer: Detailed results by occupation

	2010-2012		2017-2019		2010-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
17-2 - Engineers						
Job is high carbon	0.263*** (0.038)	0.087*** (0.019)	0.061*** (0.022)	0.014 (0.034)	0.179*** (0.017)	0.049* (0.026)
Observations	131,354	40,493	239,746	124,776	588,505	246,083
High carbon ads	2,522	867	2,031	1,417	7,982	3,557
R^2	0.13	0.75	0.1	0.62	0.1	0.6
47 - Construction and Extraction						
Job is high carbon	0.171*** (0.046)	0.082 (0.078)	0.169*** (0.024)	0.056** (0.025)	0.192*** (0.022)	0.05* (0.027)
Observations	92,652	25,341	334,835	207,864	642,275	314,734
High carbon ads	2,701	1,038	8,421	6,232	16,057	9,494
R^2	0.17	0.76	0.16	0.74	0.18	0.7
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes		Yes		Yes

Notes: We estimate the specifications of Table 4 on each of our two high-carbon occupations by splitting the sample. Standard errors are clustered at the CZ level.

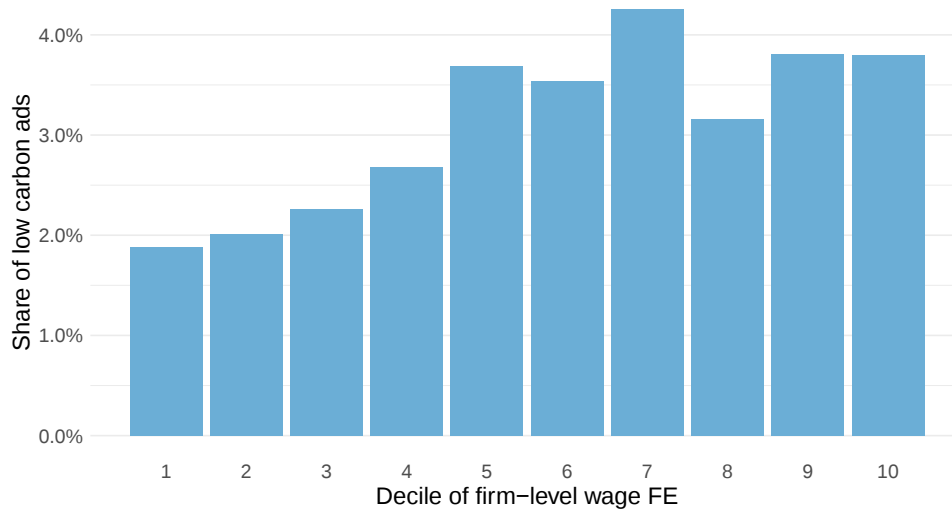


Figure G.2: Firm-level share of low-carbon ads by decile of firm-level wage FEs

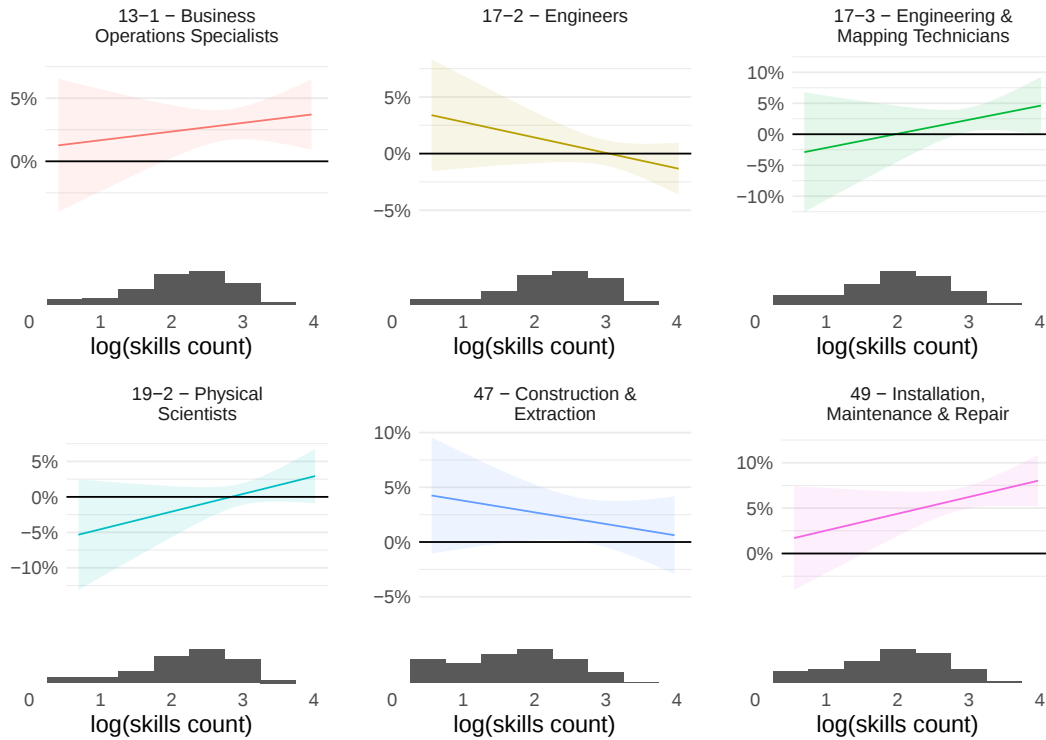
Notes: Firm-level FEs are recovered by regressing the log of the offered salary on firm FE, controlling for year, skill vector length, commuting zone and SOC (3-digits) FEs. Firms are then grouped by decile of these recovered FEs, with the share of low-carbon ads advertised by these firms computed.

Table G.10: Returns to ad complexity

	2010-2012	2017-2019	All years
	(7)	(8)	(9)
Job is low carbon	-0.027 (0.052)	-0.018 (0.020)	0.012 (0.016)
log(Skills count)	0.052*** (0.005)	0.065*** (0.002)	0.063*** (0.002)
Job is low carbon log(Skills count)	0.032* (0.019)	0.019** (0.007)	0.010* (0.006)
Observations	273,544	1,600,343	2,578,408
R^2	0.74	0.69	0.66
Year FE	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The estimation sample is restricted to ads where we observe the name of the advertising firm, within our six occupations of interest. Controls include year, skill count bins, CZ, 3-digits occupation codes and firm FE – identical to columns (3) and (6) in Table 4. Standard errors are clustered at the CZ level.

**Figure G.3:** Marginal effect of job ad complexity on low-carbon wage gap by SOC group

Notes: The specification of Table C.10 is estimated for each of our six main occupations over 2010-2019. The plotted line represents the marginal effect of the log of skill vector length on the low carbon wage premium. Shaded areas are 95% confidence intervals, with standard errors clustered at the CZ level.

Table G.11: Returns to ad complexity & broad skills (log count)

	2010-2012	2017-2019	All years
	(7)	(8)	(9)
Job is low carbon	0.045*** (0.017)	0.044*** (0.006)	0.058*** (0.006)
log(Meta-cognitive)	0.027*** (0.005)	0.036*** (0.003)	0.035*** (0.003)
log(Meta-social)	0.056*** (0.007)	0.072*** (0.003)	0.076*** (0.003)
log(Technical)	0.052*** (0.006)	0.049*** (0.002)	0.052*** (0.002)
Job is low carbon log(Meta-cognitive)	-0.036** (0.016)	-0.040*** (0.007)	-0.036*** (0.006)
Job is low carbon log(Meta-social)	0.047*** (0.013)	0.018*** (0.007)	0.011* (0.006)
Job is low carbon log(Technical)	-0.003 (0.015)	-0.013 (0.009)	-0.015** (0.006)
Observations	273,544	1,600,343	2,578,408
R^2	0.74	0.69	0.67
Year FE	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Our Mincerian wage regression is augmented by interacting the low carbon indicator with the log of the count of skills belonging cognitive (cognitive & IT), social (social & management) or technical groupings respectively in each ad. Controls include year, skill count bins, CZ, 3-digits occupation codes and firm FE. Standard errors are clustered at the Commuting Zone level.

Table G.12: Returns to ad complexity & broad skills (dummy)

	2010-2012	2017-2019	All years
	(7)	(8)	(9)
Job is low carbon	0.030 (0.018)	0.037*** (0.008)	0.050*** (0.008)
Technical	0.039*** (0.005)	0.034*** (0.002)	0.038*** (0.002)
Meta-cognitive	0.018*** (0.005)	0.022*** (0.002)	0.022*** (0.003)
Meta-social	0.038*** (0.006)	0.045*** (0.003)	0.051*** (0.003)
Job is low carbon Meta-cognitive	-0.007 (0.014)	-0.027*** (0.008)	-0.025*** (0.006)
Job is low carbon Meta-social	0.046** (0.018)	0.017* (0.009)	0.008 (0.009)
Job is low carbon Technical	0.003 (0.017)	-0.012 (0.010)	-0.013** (0.007)
Observations	273,544	1,600,343	2,578,408
R^2	0.74	0.69	0.66
Year FE	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Our Mincerian wage regression is augmented by interacting the low carbon indicator with a dummy indicating whether the ad contains any cognitive & IT (Meta-cognitive), social & management (Meta-social) or technical skill respectively. Controls include year, skill count bins, CZ, 3-digits occupation codes and firm FE. Standard errors are clustered at the Commuting Zone level.

Table G.13: Relationship between low-carbon job and wage offer by year

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Job is low carbon	0.070*** (0.018)	0.086*** (0.016)	0.089*** (0.016)	0.126*** (0.012)	0.066*** (0.011)	0.064*** (0.010)	0.097*** (0.015)	0.046*** (0.012)	0.043*** (0.008)	0.047*** (0.007)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The Mincerian wage regression of Table 4 is augmented with interactions between the low carbon indicator and a year dummy. Controls include year, skill count bins, CZ and 3-digits occupation codes. Standard errors are clustered at the Commuting Zone level.

Appendix H Spatial correlation

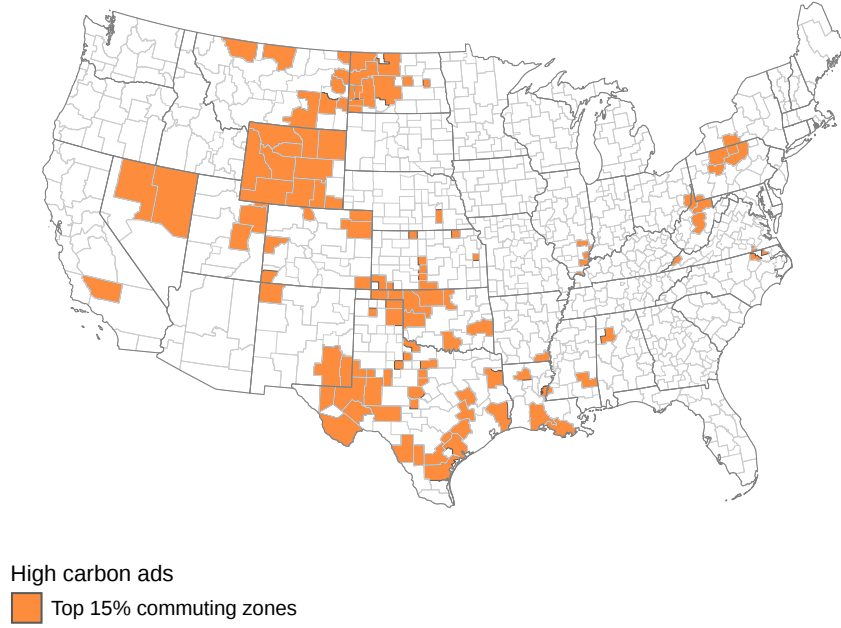


Figure H.1: Spatial distribution of high-carbon vacancies in low-skilled occupations

Table H.1: Locational Gini

	Low carbon ads	High carbon employment	High carbon ads	Generic ads
Low skill	0.33	0.98	0.69	Construction & Extraction 0.23

Notes: Table H.1 presents the Locational Gini for share of low-carbon ads per CZ, share of high-carbon employment per CZ and share of high-carbon ads per CZ. The Gini locational coefficient is calculated following Gabe and Abel (2012) using our own job ads dataset and data on employment by occupation and commuting zone from the American Community Survey adapted from Popp et al. (2021). For any of variables presented in the four columns listed above, indexed by k , it can be expressed as:

$$LocGini_k = \Delta/4u$$

where	Δ	=	$\{1/[n(n-1)]\} \sum_{i=1}^n \sum_{j=1}^n x_i - x_j $	
	i, j	=	U.S. commuting zones ($i \neq j$)	
	n	=	Total number of CZ under ERS 2000 (709)	
	u	=	mean of the share variable k across all CZ	
	$x_{i(j)}$	=	(1) [CZ i 's (j 's) share of low-carbon ads]	/ [CZ i 's (j 's) share of all ads]
			(2) [CZ i 's (j 's) share of high-carbon emp.]	/ [CZ i 's (j 's) share of all emp.]
			(3) [CZ i 's (j 's) share of high-carbon ads]	/ [CZ i 's (j 's) share of all ads]
			(4) [CZ i 's (j 's) share of SOC 47 ads]	/ [CZ i 's (j 's) share of all ads]

Table H.2: Correlation between the share of low-carbon ads and high-carbon employment

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(1 + s_{hc,cz}^{emp})$	0.178*** (0.037)	0.068*** (0.019)	0.074*** (0.023)
Observations	681	681	679
R^2	0.13	0.022	0.023

Notes: Table H.2 presents estimates of $\beta_{lc,hc}^{emp}$ in $\log(1 + s_{lc,cz}) = \beta_{lc,hc}^{emp} \log(1 + s_{hc,cz}^{emp}) + \varepsilon_{cz}$. $s_{lc,cz}$ is the average share of low-carbon ads in low skilled occupations between 2010 and 2019 in each CZ. $s_{hc,cz}^{emp}$ is the average share of high-carbon employment in low skilled occupations between 2010 and 2017 in each CZ, according to the American Community Survey (ACS). Column (1) presents unweighted results, while column (2) provides results weighted by the average number of job ads between 2010 and 2019 in each CZ and column (3) weighted by the average population per CZ between 2010 and 2019. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors clustered by CZ are provided in parentheses.

Table H.3: Correlation between the share of low-carbon ads and high-carbon ads

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(1 + s_{hc,cz}^{ad})$	0.241*** (0.062)	0.168*** (0.045)	0.189*** (0.050)
Observations	650	650	646
R^2	0.097	0.028	0.033

Notes: Table H.3 is identical to Table H.2, substituting the share of high carbon employment ($s_{hc,cz}^{emp}$) for the share of high carbon ads ($s_{hc,cz}^{ad}$).

Table H.4: Correlation between the share of low-carbon ads and annual personal income

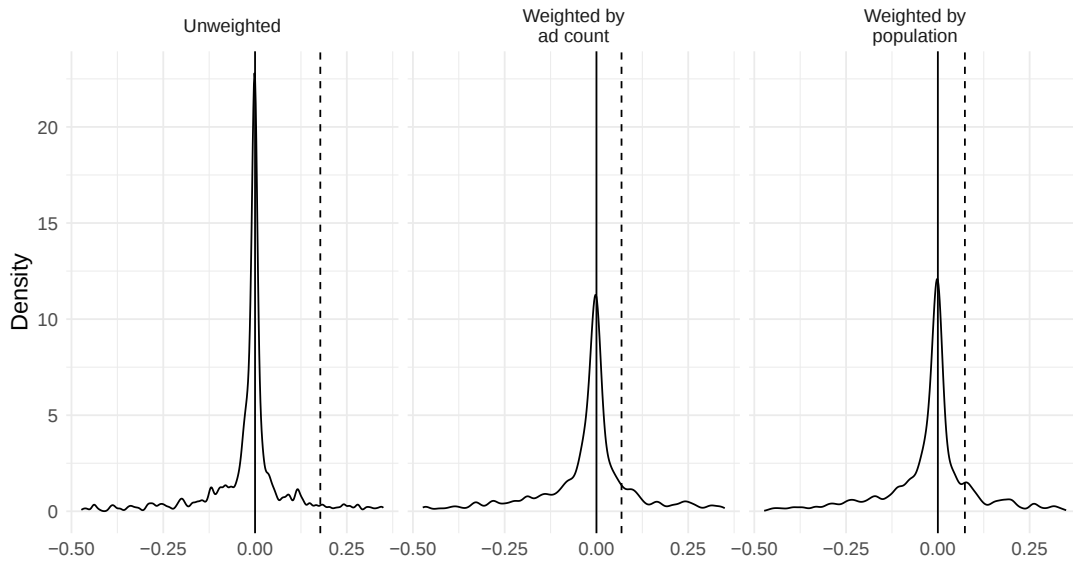
	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(inc_{cz})$	0.009*** (0.001)	0.002** (0.001)	0.002** (0.001)
Observations	679	679	679
R^2	0.075	0.026	0.025

Notes: Table H.4 presents estimates of β_{lc}^{inc} in $\log(1 + s_{lc,cz}) = \beta_{lc}^{inc} \log(inc_{cz}) + \varepsilon_{cz}$. $s_{lc,cz}$ is the average share of low-carbon ads in low skilled occupations between 2010 and 2019 in each CZ. inc_{cz} is the mean income per capita between 2010 and 2019 in each CZ. Column (1) presents unweighted results, while column (2) provides results weighted by the average number of job ads between 2010 and 2019 in each CZ and column (3) weighted by the average population per CZ between 2010 and 2019. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors clustered by CZ are provided in parentheses.

Table H.5: Correlation between the share of high-carbon ads and annual personal income

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(inc_{cz})$	0.007*** (0.003)	-0.001* (0.000)	-0.001*** (0.000)
Observations	648	648	648
R^2	0.021	0.0055	0.014

Notes: Table H.5 presents estimates of β_{hc}^{inc} in $\log(1 + s_{hc,cz}) = \beta_{hc}^{inc} \log(inc_{cz}) + \varepsilon_{cz}$. $s_{hc,cz}$ is the average share of high-carbon ads in low skilled occupations between 2010 and 2019 in each CZ. inc_{cz} is the mean income per capita between 2010 and 2019 in each CZ. Column (1) presents unweighted results, while column (2) provides results weighted by the average number of job ads between 2010 and 2019 in each CZ and column (3) weighted by the average population per CZ between 2010 and 2019. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Standard errors clustered by CZ are provided in parentheses.

**Figure H.2:** Distribution of spatial correlation between pairs of 6-digits Construction and Extraction occupations (47.0000)

Notes: Each panel presents the distribution of the pair-wise spatial correlation between the share of ads in any two occupations at the SOC 6-digits level within SOC group 47, Construction and Extraction, at the CZ level. The vertical dashed line represents the correlation between the shares of low-carbon ads and high carbon employment within SOC 47, at the CZ level. From left to right, the ad shares are unweighted, weighted by ad count and weighted by population at the CZ level resp. – the spatial correlation of interest lies at the 89th, 83rd and 84th percentile resp.

Table H.6: Top low-carbon job identifiers in low-skilled occupations by state

State	Most freq. low carbon	2 nd most freq.	3 rd most freq.
Alabama	Insulation	Emissions Testing	Energy Conservation
Alaska	Insulation	Public Transit Systems	Retrofitting
Arizona	Insulation	Energy Conservation	Solar Energy
Arkansas	Insulation	Pollution Control	Equipment Efficiency
California	Insulation	Solar Sales	Solar Energy
Colorado	Insulation	Energy Conservation	Renewable Energy
Connecticut	Insulation	Solar Sales	Solar Energy
Delaware	Insulation	Solar Sales	Solar Energy
Florida	Insulation	Energy Conservation	Retrofitting
Georgia	Insulation	Energy Conservation	Energy Efficiency
Hawaii	Energy Conservation	Insulation	Efficient Transportation
Idaho	Insulation	Clean Energy	Insulation Installation
Illinois	Insulation	Energy Efficiency	Energy Conservation
Indiana	Insulation	Equipment Efficiency	Energy Efficiency
Iowa	Insulation	Ethanol	Wind Turbines
Kansas	Insulation	Wind Turbines	Wind Power
Kentucky	Insulation	Energy Conservation	Retrofitting
Louisiana	Insulation	Energy Conservation	Energy Efficiency
Maine	Insulation	Renewable Energy	Wind Turbines
Maryland	Insulation	Energy Conservation	Energy Efficiency
Massachusetts	Insulation	Energy Conservation	Energy Efficiency
Michigan	Insulation	Energy Conservation	Energy Efficiency
Minnesota	Insulation	Energy Conservation	Energy Efficiency
Mississippi	Insulation	Energy Efficiency	Retrofitting
Missouri	Insulation	Energy Conservation	Energy Efficiency
Montana	Insulation	Insulation Installation	Geothermal
Nebraska	Insulation	Ethanol	Wind Turbines
Nevada	Energy Conservation	Insulation	Solar Sales
New Hampshire	Insulation	Insulation Installation	Solar Sales
New Jersey	Insulation	Solar Sales	Solar Energy
New Mexico	Insulation	Solar Energy	Wind Turbines
New York	Insulation	Energy Efficiency	Solar Sales
North Carolina	Insulation	Energy Efficiency	Energy Conservation
North Dakota	Insulation	Wind Turbines	Public Transit Systems
Ohio	Insulation	Retrofitting	Energy Conservation
Oklahoma	Insulation	Wind Turbines	Wind Power
Oregon	Insulation	Energy Efficiency	Energy Conservation
Pennsylvania	Insulation	Energy Conservation	Energy Efficiency
Rhode Island	Insulation	Energy Efficiency	Solar Sales
South Carolina	Insulation	Energy Conservation	Energy Efficiency
South Dakota	Insulation	Ethanol	Wind Turbines
Tennessee	Insulation	Energy Conservation	Retrofitting
Texas	Insulation	Energy Conservation	Retrofitting
Utah	Energy Conservation	Insulation	Energy Efficiency
Vermont	Insulation	Energy Efficiency	Energy Conservation
Virginia	Insulation	Energy Conservation	Energy Efficiency
Washington	Insulation	Retrofitting	Energy Efficiency
West Virginia	Insulation	Energy Efficiency	Insulation Installation
Wisconsin	Insulation	Energy Conservation	Energy Efficiency
Wyoming	Efficient Transportation	Insulation	Wind Turbines

Appendix I Robustness on the identification of low-carbon skills

Table I.1: Sensitivity of low-carbon skills set to selection hyper-parameters

Sensitivity yielding additional low-carbon skills (list of low-carbon skills added in a given sensitivity test)

a) Main specification	See main list of low carbon skills in Table B.5
b) Frequency threshold 10 percentile points less strict	Biocatalytic Processes, Bioness, Bioremediation, Biosafety, Bioswales, Brownfield Re-development, Brownfields, Catalysis, Coolant Systems, Corrective Containment, Crop Fertilization, Fertilizers, Government Incentives, Government Rebates, Heating - Cooling Systems, Heating Systems, Pipe Insulation, Plumbing Pipe Insulation, Rainwater Harvesting, Sediment Extraction, Sediment Removal, Sediment Sampling, Sedimentation Control, Sedimentation Rate, Water Conservation, Water Reuse, Water Supply and Demand, Water Use Reduction
c) Keyword threshold 10% less strict	Wastewater Lift Station Design, Wastewater Treatment Plant Design
d) Semantic threshold top 1.5%	Advanced Technologies, Clean Technology, Clean Technology Investment Opportunities, Cleantech Products, Cleantech Solutions, Cost Efficiency, Domestic Transportation Services, Efficiency Analyses and Testing, Efficiency Estimation, Financial Efficiency, International Transportation Services, Renewable Sales, Telematics, TortoiseSVN, Transportation Contracts, Transportation Finance, Transportation Sourcing, Vantive, Vehicle Systems, Vvandt, Wind Energy Project Management, Wind Energy Project Planning, Wind Project Construction, Wind Project Development, Wind Project Engineering
e) Semantic clustering threshold 10% less strict	Application Performance Management, Biofuels Production Adjustment, Biofuels Production Management, Conservation Services, Ecological Services, Emissions Analyzer Operation, Emissions Analyzers, Energy Saving Plumbing Systems, Equipment Design, Equipment Development, Equipment Implementation, Facility and Site Construction Layout, Facility Design, Facility Layout, Facility Planning Analysis, Flexible fuel vehicles (FFV), Heavy Weather Operations, Low Voltage Lighting, Performance Improvement, Performance-related conditions, Railroad Law, Railroad Operating Rules, Storage as a Service, Water Saving Plumbing Systems
f) Including ‘grey’ skill clusters	Decentralized Wastewater Management, Natural Resources, Nuclear Energy, Nuclear Industry Knowledge, Nuclear Procurement, Nuclear Safety, Soil Conservation, Soil Management, Soil Protection, Wastewater Collection, Wastewater Distribution, Wastewater Engineering, Wastewater Process Engineering, Wastewater Processing, Wastewater Purification, Wastewater Treatment

Table I.2: Sensitivity of low-carbon skills set to selection hyper-parameters (cont.)

Sensitivity yielding fewer low-carbon skills (list of low-carbon skills removed in a given sensitivity test)

g) Frequency threshold 10 percentile points more strict	Benefits Research, Biofuel Product Development, Biofuel Production, Biofuels Applications, Biofuels Development, Biofuels Extraction, Biofuels Plant Safety, Biofuels Processing, Biofuels Processing Equipment, Biofuels Research, Biofuels Research and Development, Biofuels Technology, Cost-Benefit Studies, Electric Vehicle, Ethanol, Ethanol Distillation, Ethanol Recovery Methods, Industrial Ecology, Optical Data Storage, Soil Tillers, Storage Management Technologies, Sustainable Materials, Tillage
h) Keyword threshold 10% more strict	Abatement Projects, Air Pollution Control, Air Quality Control, Air Quality Regulations, Air Quality Remediation, Air Quality Standards, Alternative Energy Design, Alternative Energy Evaluation, Benefits Research, Bicycle Planning, Bike Industry Knowledge, Biofuel Product Development, Biofuel Production, Biofuels Applications, Biofuels Development, Biofuels Extraction, Biofuels Plant Safety, Biofuels Processing, Biofuels Processing Equipment, Biofuels Research, Biofuels Research and Development, Biofuels Technology, Carbon Accounting, Carbon Asset Management, Carbon Management, Carbon Offsets, Carbon Reduction, Cost-Benefit Studies, Electric Vehicle, Emission Reduction Projects, Emissions Standards, Ethanol, Ethanol Distillation, Ethanol Recovery Methods, Heavy Rail, Heavy Rail Transit Systems, High Speed Rail, Industrial Ecology, Light Rail, Light Rail Transit Systems, Low Carbon Projects, Low Carbon Solutions, Optical Data Storage, Pollution Control, Pollution Control Equipment, Pollution Control Systems, Pollution Prevention, Pollution Regulation, Public Transit Operations, Public Transit Systems, Public Transportation System, Rail Equipment Maintenance, Rail Equipment Repair, Rail Industry Knowledge, Rail Operations, Rail Safety, Rail-Track Laying, Railroad Conducting, Railroad Design, Railroad Engineering, Railroad Safety, Railway Signaling, Railway Systems, Smoke Emissions Reduction, Soil Tillers, Storage Management Technologies, Sustainable Materials, Tillage, Transit Systems, Wind Commissioning, Wind Consultation, Wind Energy Industry Knowledge, Wind Energy Operations, Wind Energy Operations Management, Wind Field Operations, Wind Generator Assembly, Wind Turbine Control System, Wind Turbine Equipment, Wind Turbine Equipment Testing, Wind Turbine Fabrication, Wind Turbine Performance Improvement, Wind Turbine Service
i) Semantic threshold top 0.5%	Air Quality Regulations, Air Quality Standards, Cooling Efficiency, Emissions Standards, Energy Cost Reduction, Energy Supply Side Savings, Heating Efficiency, Insulation Efficiency, Streetcars, Trams, Wind Commissioning, Wind Consultation, Wind Field Operations
j) Semantic clustering threshold 10% more strict	Bike Industry Knowledge, Electricity Regulation, Emissions Inspection, Emissions Testing, Energy Law, Energy Loss Calculation, Ethanol Distillation, Ethanol Recovery Methods, Mitigation Projects, Performance Yield, Photovoltaic Mounting Solutions, Photovoltaic (PV) Module Evaluation, Pollution Control Equipment, Pollution Control Systems, Public Transit Operations, Public Transit Systems, Public Transportation System, Smoke Emissions Reduction, Spray Foam (Insulation), Storage Management Technologies, Transit Systems

Table I.3: Sensitivity of low-carbon vacancy shares to low-carbon skills selection

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)
All occupations	0.87%	1.12%	0.85%	0.94%	0.98%	1.13%	0.85%	0.77%	0.86%	0.81%
High-skilled occupations	0.30%	0.35%	0.29%	0.34%	0.36%	0.41%	0.29%	0.27%	0.30%	0.29%
Low-skilled occupations	0.57%	0.77%	0.55%	0.61%	0.61%	0.72%	0.55%	0.50%	0.56%	0.53%

Table I.4: Sensitivity of low-carbon skills premium to low-carbon skills selection

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)
13-1 - Business Operations Specialists	1.561*** (0.228)	1.489*** (0.211)	1.591*** (0.232)	1.85*** (0.205)	1.797*** (0.207)	1.536*** (0.201)	1.59*** (0.232)	1.883*** (0.242)	1.567*** (0.229)	1.644*** (0.237)
17-2 - Engineers	2.623*** (0.157)	2.601*** (0.141)	2.667*** (0.159)	2.472*** (0.141)	2.722*** (0.118)	2.246*** (0.13)	2.67*** (0.16)	2.735*** (0.173)	2.634*** (0.157)	2.666*** (0.159)
17-3 - Engineering and Mapping Technicians	2.953*** (0.227)	2.771*** (0.184)	2.991*** (0.231)	2.905*** (0.209)	3.101*** (0.187)	2.636*** (0.173)	2.988*** (0.231)	3.102*** (0.271)	2.969*** (0.231)	3.045*** (0.237)
19-2 - Physical Scientists	2.379*** (0.23)	2.468*** (0.222)	2.371*** (0.232)	2.396*** (0.225)	2.412*** (0.231)	2.532*** (0.167)	2.372*** (0.232)	2.146*** (0.23)	2.419*** (0.231)	2.351*** (0.235)
47 - Construction and Extraction	2.693*** (0.24)	2.612*** (0.204)	2.696*** (0.242)	2.705*** (0.239)	2.731*** (0.233)	2.719*** (0.214)	2.696*** (0.242)	2.701*** (0.251)	2.694*** (0.241)	2.696*** (0.236)
49 - Installation Maintenance, and Repair	2.618*** (0.424)	2.674*** (0.346)	2.669*** (0.432)	2.499*** (0.366)	2.553*** (0.404)	2.617*** (0.386)	2.669*** (0.432)	2.752*** (0.449)	2.661*** (0.429)	2.744*** (0.453)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table I.5: Sensitivity of low-carbon wage premium to low-carbon skills selection

	2010-2019									
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
Job is low carbon	0.037*** (0.004)	0.014*** (0.004)	0.035*** (0.004)	0.035*** (0.004)	0.040*** (0.004)	0.027*** (0.004)	0.035*** (0.004)	0.041*** (0.004)	0.038*** (0.004)	0.036*** (0.004)
Observations	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408	2,578,408
R^2	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Skill vector length FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOC (3-digits) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

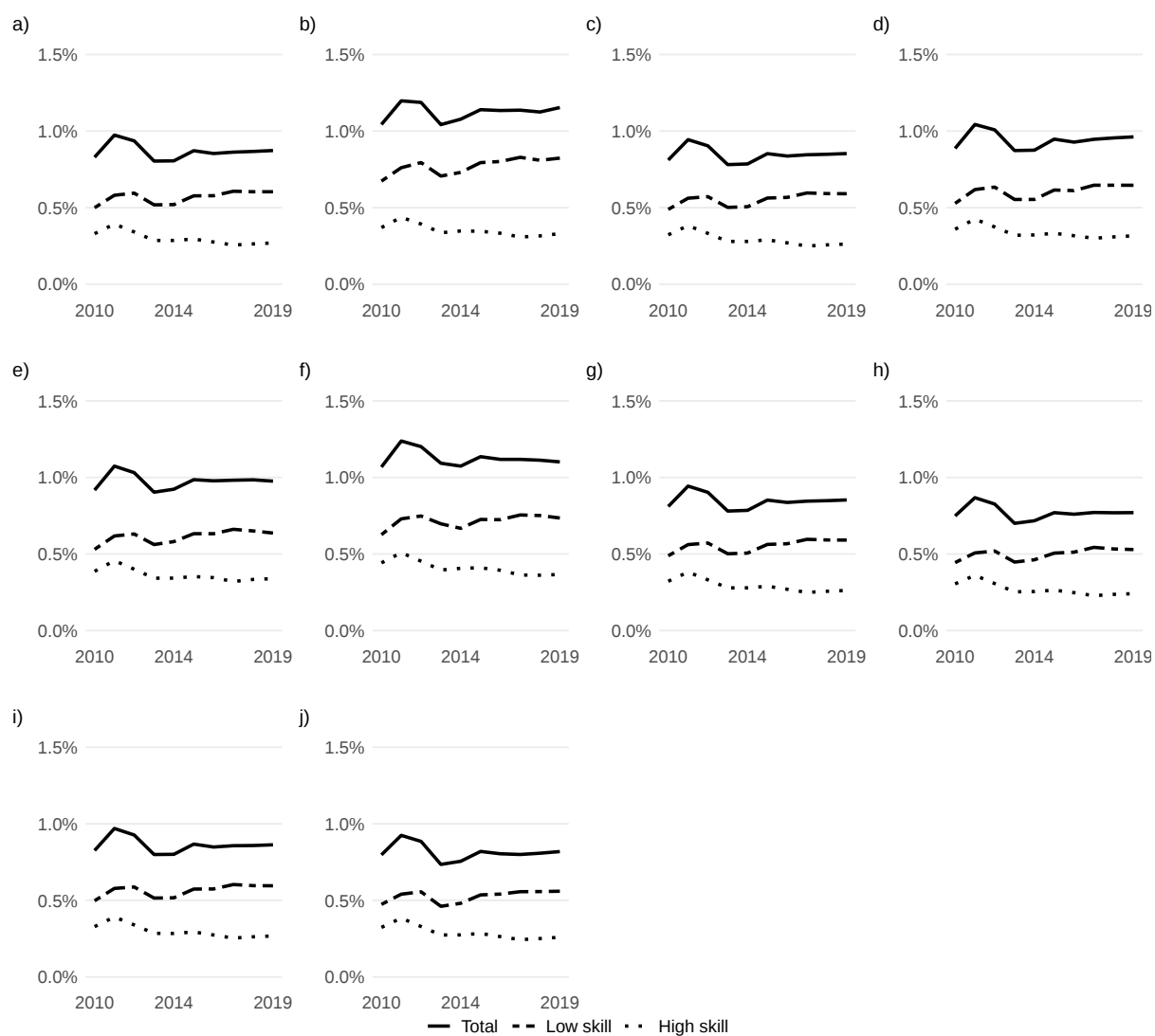


Figure I.1: Sensitivity of low-carbon vacancy shares to low-carbon skills selection

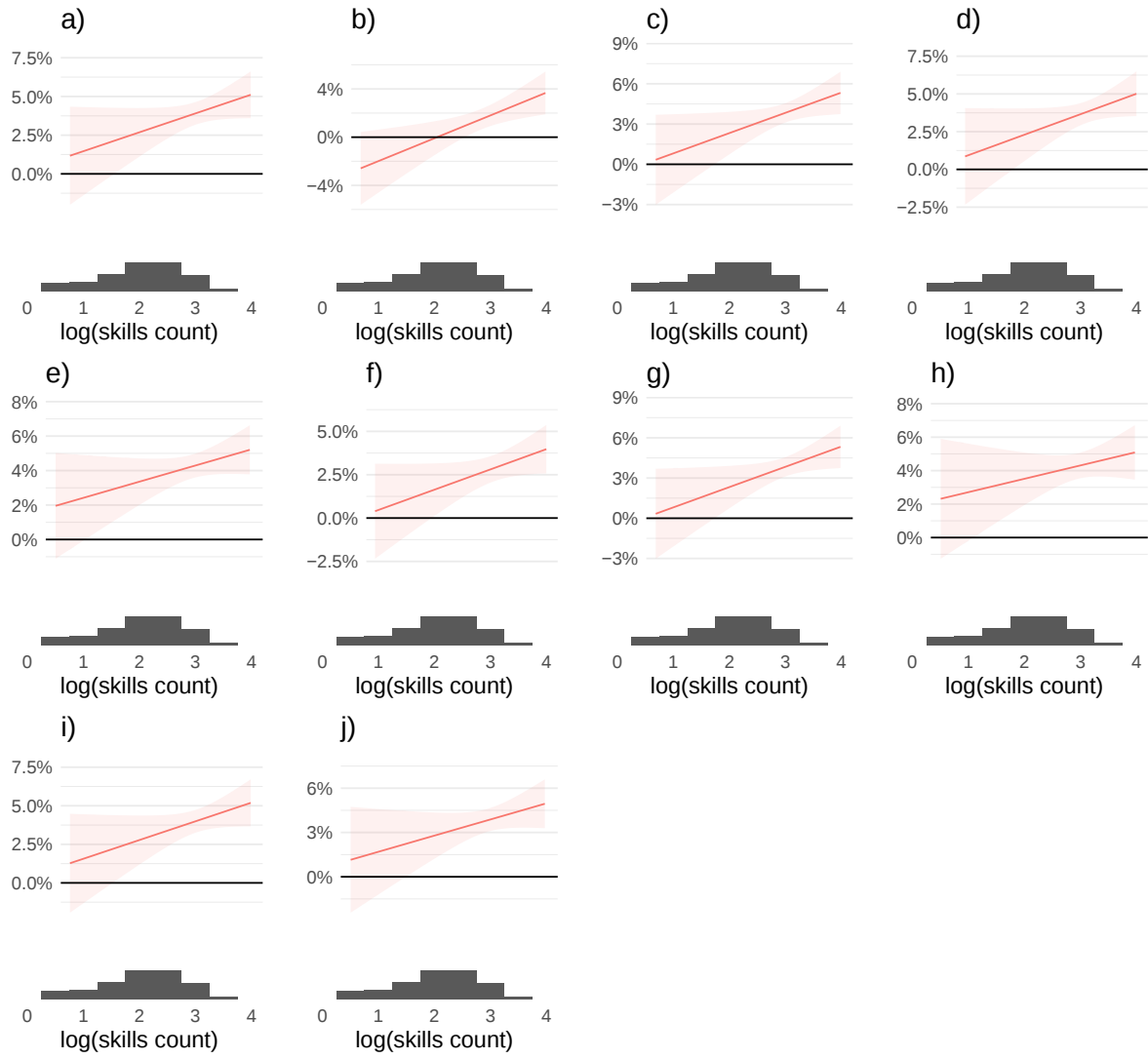


Figure I.2: Sensitivity of returns to complexity to low-carbon skills selection

Appendix J Robustness: benchmarking the skill-based measure against task-based classifications

J.1 Methodology

Task-based benchmark. Following Vona et al. (2018), let g_k denote the *greenness* of six-digit occupation k , defined as the share of O*NET specific tasks tagged “green” in that occupation. Aggregating g_k with BLS employment weights yields an economy-wide employment share of green jobs, as employed in the present article and widely in the literature (e.g. Elliott and Lindley, 2017; Vona et al., 2019).

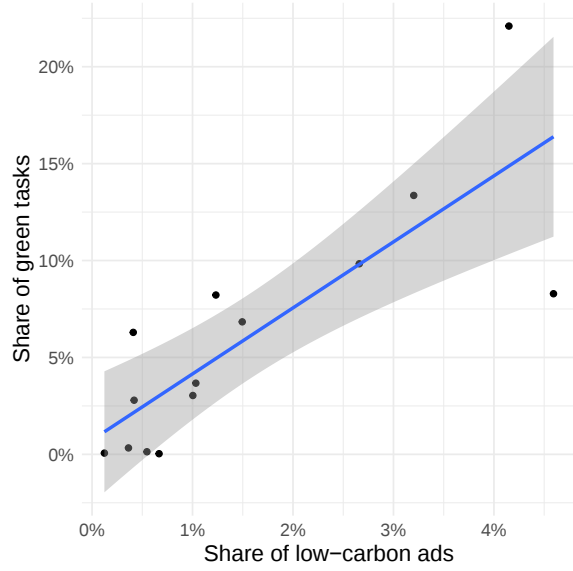
Replication of Vona et al. (2018). We replicate the procedure described by Vona et al. (2018) exactly to obtain 6-digits SOC code-level green task shares. In particular, we take care in applying the corrections identified by Vona et al. (2018) in their Appendix Table A1. We then apply combine these SOC code-level green shares with the same BLS employment weights used throughout the rest of the paper to obtain a task-based green job share of 3.2% (see J.1).

Low-carbon restricted task list. Many O*NET green tasks concern activities (waste, remediation, water) that do not directly lower greenhouse-gas emissions, and therefore fall outside the scope of our low-carbon skill identification algorithm. We thus hand-coded a subset of tasks that unambiguously target mitigation technologies (renewables, efficiency, electrification, carbon accounting). Applying the same steps to this “low-carbon task” subset produces a more comparable task-based benchmark, and yields a low-carbon job share of 1.5%.

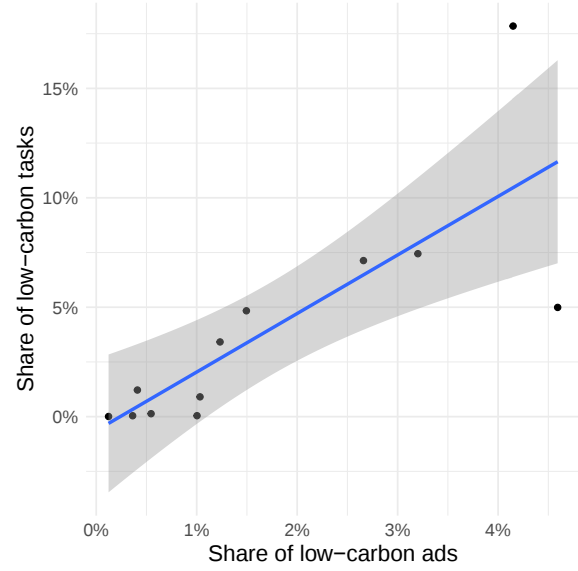
Skill-based measure Section 2 of the paper sets out how 389 low-carbon skills are identified with NLP techniques; a vacancy is low-carbon if it contains at least one of these skills. As mentioned in the main body of the article, our approach yields a low-carbon job share of 0.9%.

J.2 Correlation between the task-based and skill-based approaches

Figure J.1 plots, for the 12 two-digit SOC groups with non-zero O*NET green task shares, the share of low-carbon ads against the task-based greenness index. Both panels reveal positive and statistically significant correlations, of 0.63 and 0.59 respectively. The intercept remains close to zero, indicating the absence of systematic bias in our skill-based methodology.



(a) Full O*NET green task list



(b) Restricted low-carbon task list

Figure J.1: Skill- vs. task-based low-carbon employment shares, SOC two-digit level (2010–19)

Table J.1: Employment share of green / low-carbon jobs, 2010–19 average

Scope	Measure	Definition	Share
Green	Task-based	Full O*NET green task list	3.20 %
Low-carbon	Task-based	Restricted low-carbon task list	1.50 %
Low-carbon	Skill-based	Ad with ≥ 1 low-carbon skill	0.90 %

J.3 Aggregate comparison

Table J.1 shows that the broad task-based estimate yields a green employment share of (3.2%), consistent with earlier studies. Restricting the task universe to mitigation activities halves that estimate to 1.5%, bringing it much closer to the 0.9% delivered by our skill-level approach. The convergence supports the view that our NLP classification captures essentially the same set of jobs, while discarding non-mitigation activities.

This comparison thus validates the robustness of both our methodological contribution and of our estimates of low-carbon employment shares.

See O*NET release 26.1; mappings to 2010 SOC codes are described in Appendix B of [Vona et al. \(2018\)](#).
SOC groups with zero green tasks in the O*NET classification are dropped; the shares are obtained within each SOC group from SOC 6-digit shares weighted by BLS employment.