Who's fit for the low carbon transition? Emerging skills and wage gaps in job vacancy data

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Abstract

Much of the uncertainty around the labour market impacts of the low carbon transition can be attributed to a basic problem in identifying the jobs that drive the transition forward and the skills required by these jobs. We move beyond previous occupation-level analyses using the near universe of online job vacancies data published between 2010-2019 in the U.S., to develop a novel methodology to precisely identify low carbon jobs. The share of low-carbon ads in the US economy remains low at 1.3%, but growing in low-skilled and declining in high-skilled occupations. By comparing skill profiles of low carbon jobs to similar jobs within the same occupation, we reveal higher complexity and heterogeneity of possible reskilling patterns for the low carbon transition that was not evident under more aggregate level analysis. We show that the green skill gaps are larger, and broader than previously considered. Emphasis on technical skills is a particularly distinguishing characteristic of all low-carbon intensive occupations, but in most cases greener ads also have higher cognitive, managerial, social and IT skill requirements than similar ads. Our econometric analysis of the low-carbon wage premium suggests that it declined substantially over time and across most occupations. Focusing on the transition between high- and low-carbon jobs in engineering and construction occupations, high-carbon ads pay significantly higher wages than low-carbon ads, but the geographical and skills proximity between suggests that labor reallocation costs of the transition need not be particularly high.

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1 Introduction

Reaching climate neutrality by mid-century requires a deep transformation of all economic sectors (Rockström et al., 2017; Geels et al., 2017). In parallel with ongoing trends such as automation and globalisation (Autor, Levy and Murnane, 2003), the low carbon transition reshapes labour markets, by reallocating workers towards low carbon activities whilst skills demanded by high carbon activities may be lost with job displacement. The political imperative of supporting a "just transition" addressing the needs of workers and communities of high-carbon industries is acknowledged as a key priority to enhance the political acceptability of climate action around the world, for example by the Glasgow Agreement. However, with a few exceptions (Walker, 2013; Vona et al., 2018; Castellanos and Heutel, 2019), reallocation costs associated with retraining and reskilling are often neglected in most empirical and theoretical analyses of the labour market impacts of environmental policies (Greenstone, 2002; Morgenstern, Pizer and Shih, 2002; Kahn and Mansur, 2013; Hafstead and Williams III, 2018; Metcalf and Stock, 2020). Practically, while most vulnerable jobs linked to fossil-fuels extraction and production are straightforward to identify, conceptual issues and data limitations make it significantly more difficult to define the jobs that will benefit the most from ambitious climate policies, such as green deal plans. This may have led to overstate the job destruction effect of environmental policies in the public debate, simply because the job creation effect is more difficult to observe.

In light of these statistical and conceptual difficulties in measuring occupational exposure to green technology, the "green job" literature lacked academic rigor and have been mostly confined to the gray policy literature (Strietska-Ilina et al., 2012; Kruse et al., 2017). Recent research partly overcomes these limitations combining insights of task-based approach to labour markets (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011) with occupation-level data from the Green Economy Program of the Occupational information network (O*NET) (Consoli et al., 2016; Vona et al., 2018; Bowen, Kuralbayeva and Tipoe, 2018; Vona, Marin and Consoli, 2019). Using this approach, a nuanced measure of occupational exposure to green technologies and productions is obtained as the share of green tasks over total tasks (Vona et al., 2018). The most distinct feature of greener occupations relative to similar ones is to rely heavily on technical and engineering skills to solve and implement solutions to specific environmental problems, but also on managerial skills to organise the implementation and monitoring of environmental impacts (Vona et al., 2018).

Still, O*NET data lack granularity to look at specific environmental technologies, hence these studies stack together sectors that may have little in common in terms of skill requirements such as renewable energy technologies, waste management and environmental remediation activities. These limitations prevent to conduct rigorous analyses of the labour market implications of the low-carbon transition. Particularly, without being able to accurately identify low-carbon jobs, we can not know whether workers moving to low-carbon activities can transfer skills into new roles or need additional skills. Because the costs of job-to-job moves are proportional to the differences in skill requirements (Gathmann and Schönberg, 2010), the emergence of potential skill gaps alter the aggregated costs and benefits of the low-carbon transition. As an additional limitation, the O*NET Green Economy Program has never been updated since 2009, making it difficult to use such data to inform retraining policies based on the evolution of skill gaps in emerging and new occupations such as green ones.

Online job vacancy data become the frontier in economic research to study a broad range of labour market adjustments to technological change and other structural transformations (Deming and Kahn, 2018; Hershbein and Kahn, 2018; Deming and Noray, 2020; Azar et al., 2020; Acemoglu et al., 2020), but they have never be used to study the changing demand for skills in relation to emerging low carbon jobs. This study fills this gap by using job vacancy data and a new methodology to identify job ads related to low-carbon activities. To this end, we use a database of online job vacancies from Burning Glass Technologies (hereafter, BG), which consists of approximately 200 million job ads or the near-universe of online job ads posted in the US between 2010 and 2019. We develop a three step methodology that exploits the rich text content of online job adverts, applying a weakly supervised natural language processing to precisely identify low-carbon job vacancies engaged in developing, producing and installing low-carbon technologies. Grounded in the task-based approach to labour markets (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011), and taking advantage of the high density of green job ads in particular occupations, this approach allows us to directly isolate differences in low carbon jobs' skill requirements, wages and geographical distribution vis-à-vis fossil-fuel or other jobs within a narrow SOC occupation and to estimate the low-carbon wage premium while controlling for occupation and industry level trends. Our approach overcomes issues of data granularity and provides a very accurate and up to date characterisation of the emerging labour market dynamics and skill requirements of the low carbon transition. A key advantage of it is that it can be easily replicated in different countries and regions outside the US, adapting the definition of low-carbon ads to the country's economic structure and technological development.

2 Identifying low carbon jobs

The carbon footprint of industrial or firm productions allows a straightforward identification of the jobs that are vulnerable to climate policies. Identifying the jobs who will gain is more challenging as they are generally not employed in sectors or activities that have lower emission intensities. Jobs with low carbon footprints are normally in the service sector where there is little need to develop solutions to reduce the carbon footprint of the whole economy. In turn, building a wind turbine or a smart grid can have a high carbon footprint in the construction phase, but have substantial potential to eliminate emissions over the rest of the life-cycle. The task-based approach allows to capture the greenness of an occupation or of a job vacancy using the detailed description of what the worker is expected to do, which ultimately depends on the technology in use.[1]. For instance, we can know if a car repairer is green or not by having information on the type of engine, an information that may be available in job ad data. In less obvious cases, e.g. public transportation, it may be required an expert judgement leading to a common understanding of the technologies and organizational practices that have a potential to reduce carbon emissions.

We develop a new method of identifying low-carbon job vacancies that allows to isolate what is unique about jobs in the low carbon economy vis-á-vis conventional jobs. The method is similar to the bag of words model used by (Atalay et al., 2020), but augmented by a round of expert elicitation for the expression to resolve usual ambiguities and disagreements regarding what is green.

In the following, we present our three-step methodology. We first identify a set of valid low-carbon keywords from reliable source text usable as a benchmark to define what is low-carbon. We then assign a low-carbon score to each job ad descriptor in the BG dataset and finally cross-check this score against a cut-off level through expert elicitation. To simplify the second step of the procedure, we apply natural language processing to the expressions defining the 16,000 individual skills and tasks pre-defined by BG rather than to the full text of the job ad directly. This allows us to label such skills and tasks as low-carbon or not. A low-carbon job

[1] A few early papers compute the share of green jobs using the share of production of goods reducing harmful environmental impacts (Becker and Shadbegian, 2009; Elliott and Lindley, 2017). However, such approach does not allow to identify the workers within a sector or a company mostly engaged in greener productions.

vacancy is defined as a vacancy containing at least one low-carbon skill in its vector of skills.

2.1 Low-carbon keywords

The first step in our procedure involves the identification of keywords associated with low-carbon tasks and products. To this end, we obtain textual descriptions of all individual tasks identified in the O*NET occupational classification. As part of its Content Model, O*NET provides a comprehensive description of occupational requirements expected to perform each of the 867 detailed occupations identified under the BLS Standard Occupational Classification (SOC). In particular, this characterization includes a list of *tasks*, each of which is described by a short text. Examples include:

- "Prepare or present technical or project status reports."
- "Calibrate vehicle systems, including control algorithms or other software systems."
- "Measure and mark cutting lines on materials, using a ruler, pencil, chalk, and marking gauge."

Since 2010, a subset of these tasks have been labelled as 'green' under the O*NET classification. We exclude the category "Recycling and Waste Reduction", as it is not strictly climate-related. However, we keep the following categories: "Agriculture and Forestry", "Energy and Carbon Capture and Storage", "Energy Efficiency", "Energy Trading", "Environment Protection", "Governmental and Regulatory Administration", "Green Construction", "Manufacturing", "Renewable Energy Generation", "Research, Design, and Consulting Services", "Transportation". Examples include:

- "Calculate potential for energy savings."
- "Fabricate prototypes of fuel cell components, assemblies, or systems."
- "Test wind turbine components, by mechanical or electronic testing."

We first tokenize the task descriptions, keeping only nouns, adjectives, verbs and adverbs. We then apply natural language processing (NLP) using the term frequency–inverse document frequency (TF-IDF) algorithm Mihalcea and Tarau (2004) to the non-climate and climate subsets of tasks. This yields a relevance score comprised for every keyword in each of the two subsets. For each keyword in the climate subset, we then take the difference in the relevance score obtained within the climate subset of tasks and the one obtained in the non-climate subset (assuming a non-climate score of 0 if the keyword only appears in the climate subset). This step provides us with a climate relevance score for each keyword appearing in the O*NET task descriptions.

We apply a similar approach to the PRODCOM classification by contrasting the textual descriptions of climate change mitigation relevant products identified by Vona, Marin and Consoli (2019) with that of non-climate relevant products.

We then combine the two lists, ranked by low carbon relevance score defined above. We keep the top 250 of these to get a set of *low carbon* (climate-related) keywords that we can match against the 16,000 individual job identifiers (or 'skills') available in the Burning Glass Technologies (thereafter BGT) job ad dataset.

2.2 Low carbon job identifiers

For the non-supervised portion of our selection algorithm, we then proceed to match our list of low carbon keywords with each of the BGT job identifiers. To maximize the reliability of this matching, we resort to another NLP approach with word embeddings. Specifically we apply the Word2Vec algorithm Rong (2014) to obtain a semantic match between our low-carbon keywords and the textual descriptions of the BGT identifiers.

A direct match against the top 20 most climate-relevant keywords according to our previous algorithm identifies the first 396 of our low carbon job identifiers. A zero matching score identifies non-low carbon job identifiers, which represent the overwhelming majority of the cases. Yet, we find that approximately 600 end up in an intermediate situation, with a high yet imperfect matching score. These cases cannot be settled by our unsupervised classifier. We therefore turn to expert elicitation.

Expert survey. To resolve ambiguous cases, we have implemented a survey of 50 climate researchers recruited from leading institutions such as Oxford University, the London School of Economics, the OECD and the University of Venice among others. The email sent to each expert is included below.

Each expert received a selection of 120 job identifiers to classify as low carbon or non-low carbon. 100 of these were randomly sampled for the set of 600 ambiguous identifiers described above. 20 were sampled from the 396 low carbon identifiers found through a perfect match with our low carbon keywords. This latter subset was included to serve as a check on the quality of the expert's classification skills.

We exclude responses which failed to classify correctly more than 40% of these placebo identifiers. We then combine these returns to calculate an average low carbon score for each identifier surveyed using the following scoring scheme: 1 for 'Yes', 0.25 for a blank response, and 0 for 'No'. We finally apply a 90% threshold to recover a further 51 low carbon job identifiers. See Table A2 for the 50 most common low carbon identifiers in the dataset.

2.3 Low carbon ads

We then define as low carbon any ad that contains *at least* one of the 447 low carbon job identifiers we determined through the algorithms described above (considering the fact that the median skill length of a job ad is 7). See Table A1 for examples of low carbon ads.

Using this definition, we identify 1.8 million low carbon jobs ads of the 196 million in our sample. Because low-skill occupations are under-represented in BGT data (Deming and Kahn, 2018), we improve statistical representativeness in the following by weighting job ads in a given 6-digit occupation by the corresponding employment share of that occupation provided by the Bureau of Labor Statistics (BLS).

3 Evolution of demand for low-carbon jobs

We begin by characterising the evolution of low carbon jobs in the US economy between 2010 and 2019. Figure 1A documents a quite stable share of low-carbon job ads at around 1.35 percent of total online job vacancies over the last decade. The share of low-carbon ads exhibits a mild increase in the first three years (from 1.32% to 1.44%), followed by a decline below 1.3% in the central period and another increase from 2017 on. The initial spike aligns with the timing of the job creation effect of green part of the spending of the American Recovery and Reinvestment Act (ARRA) (Popp et al., 2021). It is important to note that job vacancy shares capture the flow of new potential jobs rather than the stock.[2] However, we are reassured by the fact that our estimate as well as the trends is in the ballpark of previous estimates of the share of green jobs (Becker and Shadbegian, 2009; Elliott and Lindley, 2017; Vona, Marin and Consoli, 2019; Popp

[2] A 1.35% share of new low-carbon vacancies is equal to a steady state stock of low-carbon jobs only if: i. The job filling rate is equal to 1; ii. The job destruction rate is the same for low-carbon and non low-carbon occupations.

et al., 2020*a*). This paper concentrates on the workforce associated with low-carbon activities rather than the entire spectrum of activities reducing environmental impacts, whereas previous studies cover a broader range of environmental activity including water and waste. This explains the smaller share of green jobs with respect to the occupation-based estimates of the share of green jobs using O*NET (around 3%, see Vona, Marin and Consoli (2019)). In spite of the fact that the BG data are not representative of the entire population, our definition of low-carbon ads produces estimates that are consistent with previous measures of green employment.

Importantly, Figures 1A also shows that the decennial trends are divergent between high-skill occupations, which experience a robust decline from 0.36% to 0.30%, and low-skill occupations, which exhibit an upward trend from 0.97% to 1.12% (see also Table B4 in the Appendix). The decline in the opening of low-carbon, high-skilled positions may have reduced their attractiveness for the most talented workers. Such decline also resonates with the decline in low-carbon patents filled by US inventors over the last decade (Popp, 2019; Probst et al., 2021). The upward trend in low-skilled, low-carbon position resonates with the job creation effect of green ARRA spending that was concentrated in manual occupations (Popp et al., 2021). An increase in the demand of unskilled workers in low-carbon activities may contribute to offset the secular deterioration of the labour market conditions for this category of workers, which is largely unrelated to environmental regulation and climate policies (Marin and Vona, 2019).

The distribution of low-carbon ads is not uniform across occupations. Table B1 in the Appendix shows that the share of low-carbon ads over total ads is higher than the average in six 2-digit SOC occupations: 1.7% Business and Finance 3.6% (SOC 13); Architecture and Engineering 4.1% (SOC 17); Life, Physical and Social Science (SOC 19); Construction and Extraction 4.1% (SOC 47); Installation, Maintenance and Repair 2.6% (SOC 49) and Transportation 7.3% (SOC 53). With the exception of Transport jobs, the same occupations are the most green-task intensive using the O*NET dataset (Vona, Marin and Consoli, 2019). Transport occupations appear to be low-carbon intensive here because "public transportation" and "bus driving" are two keywords used to identify low-carbon ads.

A 2-digit occupational grouping does not suffice in accounting for heterogeneity in occupational greenness. Indeed, substantial variation in low-carbon intensity across occupations is observed even within each 2-digit group (Table B2 in the Appendix). For instance, among the Business and Finance occupations (SOC 13), only Business Specialists (SOC 13-2) have a high share of low-carbon ads. [3] Because we are interested in comparing low-carbon and non low-carbon ads in terms of skill requirements, we focus on the five high-skilled occupations at the 3-digit SOC level that have a significant share of low-carbon ads (Business Specialists, Architects, Engineers, Technicians, Physical Scientists).[4] For low-skilled occupations, we consider the three two-digit SOC groups with high intensity of low-carbon ads (Construction and Extraction; Installation and Maintenance; Transportation). The rationale for this choice is that switching jobs from a high-skill to another high-skill 3-digit group requires substantial formal education (i.e. from biology to physics). In contrast, switching from a 3-digit occupation to another in low-skill jobs just requires months of retraining. The key goal of "just transition" policies is to ensure that displaced workers in fossil-fuel extraction jobs (SOC 47-5) are smoothly reemployed in energy efficient construction (SOC 47-2). To examine the differences in the skill requirement of these two jobs, we kept the Construction and Extraction occupations together.

The remaining panels of Figure 1 plots the trends in the low-carbon intensity for the eight low-carbon intensive occupations that are the focus of this study. While the divergent trends between high- and low-skilled occupations is confirmed, patterns are highly heterogeneous across occupations. The decline in low-carbon intensity is only evident for Business Specialists (from 2.9% to 1.9%), Engineers (from 5.2% to 3.9%) and, to a less extent, Physical Scientists (from 8.2% to 7.9%). Architects becomes relatively greener, but the total number of ads is relatively small so these results should be taken with caution. The robust increase in the low-carbon intensity of Construction (from 3.5% to 4.6%) and Installation jobs (from 2% to 3.1%) contrasts with the flat pattern of Transportation jobs. Comparing the dotted and solid lines, the unweighted intensity of low-carbon ads is significantly smaller than the weighted intensity for most occupations, particularly Physical Scientists, Business Specialists and Transportation workers. However, in both cases, trends are quite smooth in spite of the fact that the coverage of BG data increased in later years.

[3] Among Life, Physical and Social Science (SOC 19), all scientists are low-carbon intensive with respect to the global average, but Physical Scientists (SOC 19-2) stand out with a share of 8%. Among Architecture and Engineering (SOC 17), Architects (SOC 17-1), Engineers (SOC 17-2) and Technicians (SOC 17-3) have all an intensity of low-carbon ads well above 3%.

[4] Note that Technicians (SOC 17-3) is middle skill occupation requiring both formal and on-the-job training and paying wages just above those paid in low-skill occupations. Previous research found that the demand of technicians will go up to undertake the necessary adaptation to ambitious climate policies (Marin and Vona, 2019).

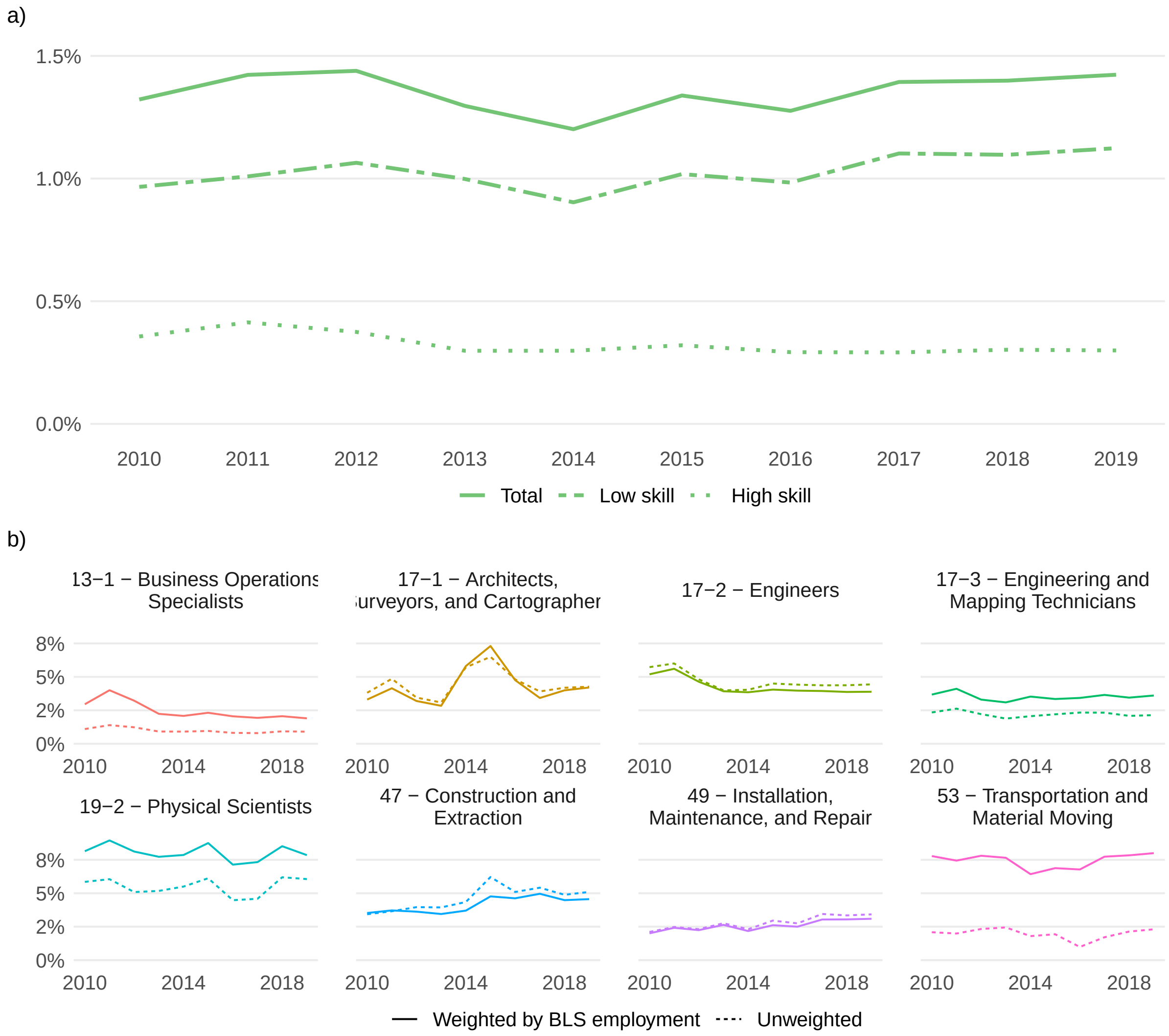

Figure 1: Evolution of low carbon ads (2010-2019)

Notes: In panels a) and b) the intensity of low carbon ads is first calculated at the 6-digit SOC occupation level as the ratio between the number of low-carbon ads and the total ads in a specific 6-digit occupation, then averaged for each reported occupational grouping weighing by 6-digits employment obtained from the U.S. Bureau of Labor Statistics. Panel a) represents the evolution of the share of low carbon ads in the entire sample, in the aggregate and for low and high skill occupations. Each subpanel in panel b) represents the evolution of the share of low carbon ads *within* each of the main eight low-carbon occupational groups. The solid line represent the low carbon share weighted by BLS employment, while the dotted line represent the unweighted share directly calculated from the sample.

4 Spatial variation in demand for low- and high-carbon jobs

Reallocation of workers from high- to low-carbon activities is the primary aspect of the labour market impacts of climate policy. Ensuring a just transition to fossil fuel workers displaced by such policies boosts political acceptability by fully neutralizing the job killing argument often used by fossil fuel lobbies and climate deniers (Vona, 2019; Weber, 2020). Spatial concentration and skill gaps are the two most important barriers to labour reallocation. Previous research highlights the high persistence of the effect of adverse deindustrialization shocks in the local labour market (Autor, Dorn and Hanson, 2016, 2021). Adverse long-term effects are larger in areas specialized in sectors exposed to the shock or lacking the adequate workforce skills. For the low-carbon transition, recent cross-occupational analyses document some geographic overlap between current fossil jobs and green competencies, but there also higher geographic concentration of green jobs in areas with higher wealth (Popp et al., 2021), high-tech activities and higher green ARRA spending (Vona, Marin and Consoli, 2019). Yet, due to the limitations of O*NET, these studies assume homogeneity in the green task content across occupations in different regions.

To explore the incidence of low-carbon job creation in locations that are likely to suffer job destruction, we contrast the geographical distribution of low and high carbon jobs in the U.S. Figure 2 displays in green the average share of low carbon online ads during the period 2010-2019 at the commuting zone level, for two occupations that exemplify low and high skilled occupations where both low and high carbon jobs are concentrated: Construction and Extraction jobs (SOC 47) and Engineers (SOC 17-2) respectively. Figure 2 overlays in hashed orange, the commuting zones with the top 15% highest concentration of high carbon jobs, averaged between 2010 and 2019. While taking an average job vacancy shares over a ten year period gives a reasonable sense of the relative employment size for these groups, in the case of high-carbon occupations which are declining over time, employment shares are more representative than job vacancy shares.

Visually, both low and high carbon jobs appear more in areas with higher natural resource endowment. The share of green jobs in Construction and Extraction is higher in areas with active solar power generation (e.g. California and Nevada) and around the wind corridor from Minnesota to Texas. The pattern is less obvious for low carbon jobs in Engineering but some states with strong renewables sectors such as Iowa and Oregon have higher concentrations. The fossil fuel jobs are spacially clustered around centres of extraction like Wyoming, West Virginia, Oklahoma and Texas and the Appalachian region (Pollin and Callaci, 2019).

We document some spacial correlation between low carbon job ads and high carbon employment for high skill occupations, but less for low skilled (Table C3). Furthermore, low carbon jobs are more concentrated in wealthier areas whereas high carbon employment shares are higher in commuting zones with lower personal income levels (Tables C1 and C2). This suggests the transition may exacerbate inequality in the U.S. particularly given low skilled workers tend to exhibit lower mobility in general. This highlights the need for targeted place based policies to prevent low skilled workers in these fossil being left behind.

We observe low carbon job ads for both occupational groups are more spread across space, suggesting the benefits of low carbon job creation will reach more areas more evenly. Locational Gini coefficients are commonly used for analysing geographic concentration and have several advantages (Krugman, 1992; Gabe and Abel, 2012). On average, we estimate a locational Gini coefficient of 0.17 and 0.16 for low and high skilled low carbon jobs respectively, indicating a similar concentration to generic ads in the same sectors (0.12 - 0.17), but considerably lower compared to high carbon employment (0.45-0.48) and high carbon ads (0.34-0.40) (Table C4). A possible explanation for the lower spacial concentration is that low-carbon engineering and construction jobs may involve activities that can be conducted distantly from the resource centres such as the design and construction of wind turbines. Relatively high degree of spacial concentration in low carbon activities has been documented in studies where the sample is restricted to renewable energy generation (Vona et al., 2018; Popp et al., 2021), suggesting the spacial dispersion found here is driven by low carbon jobs in areas such as buildings or transport.

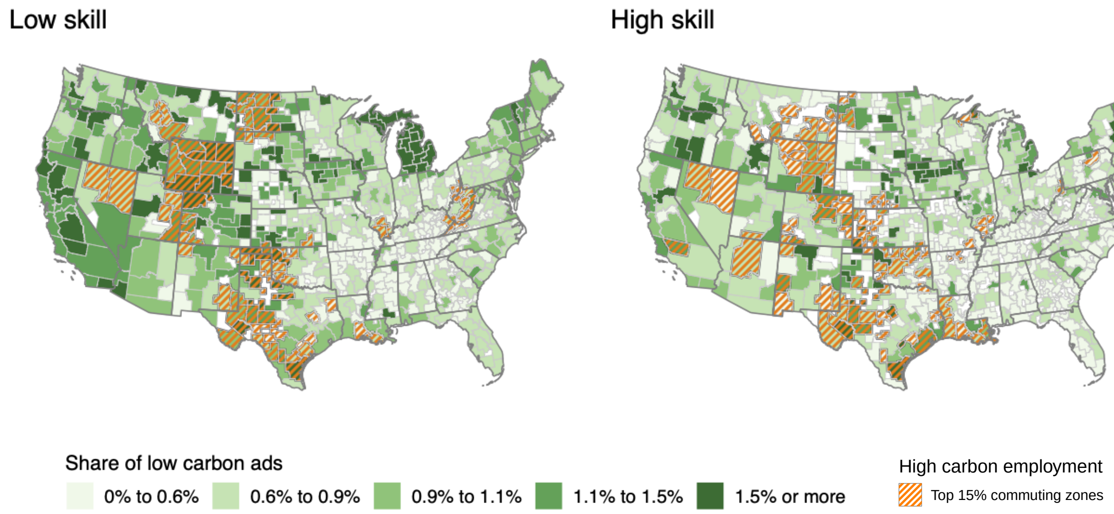

Figure 2: Spatial distribution of low carbon vacancies and high carbon jobs

Notes: Commuting zone level values for 2010-2019 average shares of unweighted low carbon job ads in green shades. Commuting zones are USDA ERS delineation (2000). Hashed orange overlay indicates top 15% commuting zones by share of high carbon employment. (A) Low carbon ads in low skilled occupations (SOC codes 31-53); high carbon employment in Construction and Extraction (SOC 47) only (B) Low carbon ads in high skilled occupations (SOC codes 11-29); high carbon employment in Engineering (SOC 17-2) only.

5 Differences in skill requirements

Labour research shows that reallocation costs are proportional to the skill similarity between occupations (Gathmann and Schönberg, 2010). We exploit here the rich information on skills contained in BG data to compare the skill content of low-carbon, fossil-fuel and other ads. We identify five skills for which retraining will be particularly costly. Those are high- and medium-skills that were found to be important for automation and the digital transformation (Autor, Levy and Murnane, 2003; Deming, 2017) as well as for the green economy (Vona et al., 2018). In particular, non-routine skills are difficult to be replaced by machines. We consider four types of non-routine skills: broad cognitive skills such as problem solving and math, IT specific skills related to the use of particular software, managerial skills linked to supervisory and leadership, social skills that encompass communication, teamwork and negotiation. In addition, we consider the main green skill: technical skills, which includes both engineering skills acquired through university education and more specific technical skills acquired in vocational schools and on-the-job training. To classify a BG skill in one of these five categories, we use a set of keywords provided by Deming and Kahn (2018) for non-routine skills and by Vona et al. (2018) for green skills.

For low-carbon, high-carbon and generic ads, Figure 3 reports the share of ads with exactly one or at least two of any of such skills for the eight main occupations that are the focus of this study. First, low-carbon ads tend to require more high-skills across all occupations. In line with Vona et al. (2018), green skill gaps are larger for technical skills and, to a lesser extent, other non-routine skills. Interestingly, the gap in technical skills is relatively narrower between low- and high-carbon than between low-carbon and generic ads, especially in construction and extraction occupations. Second, our methodology allows to reveal substantial heterogeneity across occupational groups that previous analyses were unable to detect. Low-carbon ads are high-skill intensive along all the five dimensions for technicians, physical scientists and engineers, but we do not detect large skill gaps for business specialists (except for technical skills). Also, low-carbon low-skill ads tend to have a higher skill complexity relative to generic jobs in the same occupation. For construction and extraction occupations, skill gaps are of concern for the transition from generic to low-carbon occupations, but not for the transition from high- to low-carbon occupations. Finally, skill gaps are negligible for transport but larger for technicians and installation and maintenance workers, indicating possible difficulties in filling job low-carbon vacancies in this occupational group.

Besides looking at intensity along standard skill metrics, the richness of BG data allows to search for more sophisticated reskilling patterns. In doing so, Figure 4 correlates two Balassa indexes. The index on the y-axis reports the green skill coreness: a high value implies that skill j is relatively more important in low-carbon ads than in non-low carbon ads within a given occupation. The index on the x-axis reports a generic skill coreness: a high value implies that the skill j is relatively more important in occupation k than in the rest of the economy. A positive correlation between the two indexes indicates that skills more important in low-carbon ads belong to the core skill set of that occupation, thus specialization. A negative correlation, instead, underscores a diversification pattern. For engineers (panels a and b) and construction workers (panels c and d), we observe that both low-carbon and high-carbon skills belong to the core set of skills. This implies that incremental retraining may suffice to equip existing workers with core low-carbon skills. Moreover, such retraining may be even easier for workers currently employed in fossil fuel industries. For other occupations, the patterns are more heterogeneous. The plots exhibit no correlation for architects (panel f) technicians (panel g) and installation workers (panel i), specialization among physical scientists (panel h) and diversification among business operation specialists (panel e). Combined with the previous results on skill gaps, green business requires technical reskilling that is beyond core curricula in business disciplines. For the two occupations with larger skill gaps but no specialization-diversification patterns, retraining is likely to be highly context- and technology-specific, requiring a great deal of cooperation among social actors, including trade unions, industrial associations, technical and vocational schools, to find the appropriate solutions. As well-known in the literature on varieties of capitalism, the US often lacks such high degree of cooperation between social actors compare to German-speaking and Scandinavian countries (Hall and Soskice, 2001).

Figure 3: Differences in broad skills by occupation

Notes: Each panel represents the share of ads for a given occupation and category (generic, low or high carbon) that contains *exactly one* (1) or *two or more* (2+) skills pertaining to any of the five broad skill categories listed. Percentages reported correspond to unweighted shares of ads obtained directly from the sample. The *Cognitive*, *Management*, *Social* and *Technical* broad skills are defined using sets of keywords obtained from Deming and Kahn (2018). The *IT* broad skill corresponds to the eponymous BG Technology skill cluster family.

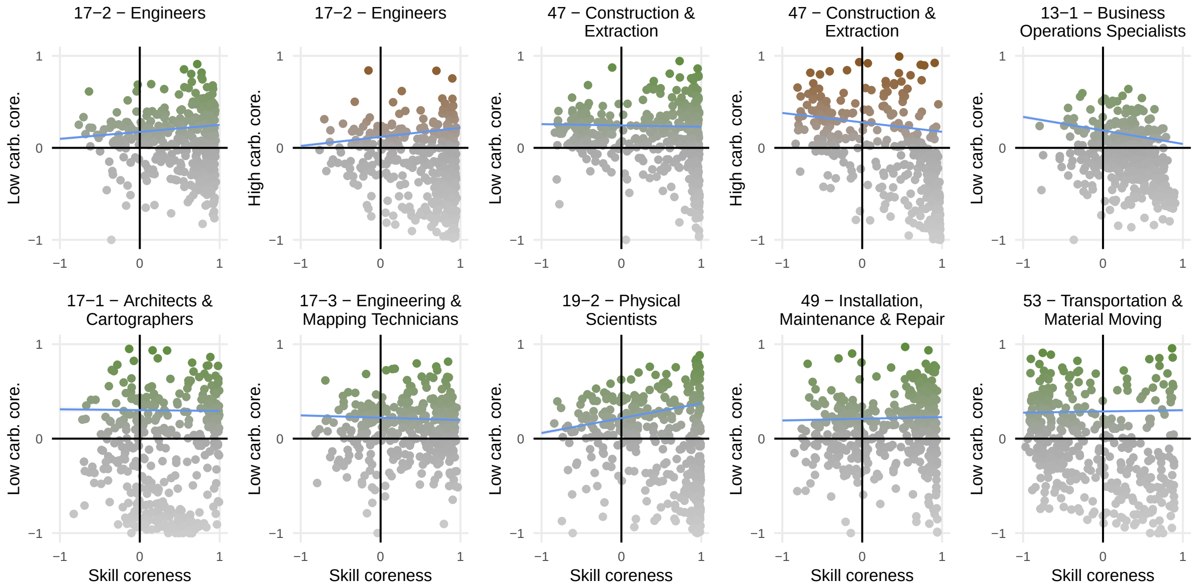

Figure 4: Specialization vs diversification by occupation

Notes: Relationship between the relative prevalence of a given skill in low (resp. high) carbon ad – low (resp. high) carbon coreness on the *y axis* – and its relative prevalence in the entire sample – skill coreness, *x axis* (see formulas below for a precise definition). Each dot represents one skill; only the 400 most frequent skills are plotted for each occupation. ρ reports the correlation between these two corenesses, obtained from a regression weighted by the share of each skill in generic ads. A significant $\rho > 0$ indicates *specialization*: skills more prevalent in low (resp. high) carbon ads tend to be core skills of the occupation. Conversely, a significant $\rho < 0$ indicates *diversification*: skills important in low (resp. high) carbon ads are not part of the occupation's core skillset.

6 The low-carbon wage premium

Wages reveal the extent to which low-carbon job ads are attractive to top talents and signal potential mismatches in low-carbon activities. Little is know regarding the green wage premium in the existing literature, with the exception of the descriptive analysis of Vona, Marin and Consoli (2019) that, however, was constrained by the use of O*NET and thus unable to measure the green premium for specific occupations. To fill this gap in the literature, we follow common practices in labour economics by estimating the low-carbon wage premium separately for the major occupational groups through multivariate regressions (see section 6.1). These regressions allow to retrieve the low-carbon wage premium holding constant other characteristics affecting wage offers, such as commuting zone characteristics, occupation and level of education.

Wage information are available for approximately 20% of job ads, thus making it difficult to consider the wage analysis presented here as representative of the US population. To mitigate these concerns, wage regressions are weighted by the employment of the 6-digit occupation in the BLS. To increase the sample size used to estimate the low-carbon wage premium, we stack the first three years together (2010-2012) and the last three years together (2017-2019). In doing so, we track the evolution of the low-carbon wage premium over time. The first period coincides with a climate policy boom of the American Recovery and Reinvestment act, which devoted substantial funds to the low-carbon transition (Aldy, 2013; Popp et al., 2021). The second period encompasses the climate policy bust of the Trump's era, with the withdrawal from the Paris agreement and a general repeal of several environmental policies, including the Clean Power Plan.

Slightly abusing of terminology, what we call low-carbon wage premium only reflects a wage offer (the demand-side) and may differ from the wage actually paid that is an equilibrium outcome, also accounting for supply-side factors such as the availability of a candidate with the required competences. Deming and Kahn (2018) and Atalay et al. (Forthcoming) circumvent this problem by combining BLS wage data with skill data extracted from job ads at the occupational level. However, such approach would only allow estimating an average low-carbon wage premium, exploiting cross-occupational variation in green tasks as in Vona, Marin and Consoli (2019). In line with the goals of characterising heterogeneity of low-carbon labour markets, we are interested in estimating occupational-specific wage premia. Our analysis complements the analysis of the skill gaps to the extent to which recruiters anticipate skill shortages and adjust the wage offers accordingly.

6.1 Wage regressions

To retrieve the low-carbon wage premium, we estimate the following equation at the job ad level (i) separately for the first (2010-2012) and the last period (2017-2019), and by main occupational groups:

$$\log(w_{it}) = \beta_{lc}\mathbb{1}\{i \in lc\} + \mathbf{X}'\theta + \mu_t + \mu_{occ} + \mu_{sec} + \mu_{CZ} + \varepsilon_i$$

where w_it is the annual wage as posted in the ad. We are interested in estimating the returns to low-carbon ad in a specific occupation, that is: β_{lc}, conditional on a set of controls. Among the controls, μ_t, μ_{occ}, μ_{sec} and μ_{MSA} are dummy variables for time (as we stack together 3 years for each period), occupation (3-digit SOC), industry (2-digit NAICS) and metropolitan statistical areas, respectively. These controls purge the low-carbon wage premium from the influence of obvious confounders, such as unobserved industry-level and regional shocks. **X** is a vector of controls. In particular, we include five dummy variables for the length of the skill vector in the job ad, which, together with the educational level required in the ad, captures both the complexity of the job post and the differences in advertising styles across companies.

Our estimate of the low-carbon wage premium cannot be interpret as a causal impact of switching to low-carbon activities on wages. Because we only observe the wage posted in the ad and not the actual wage paid when the vacancy is filled, unobserved workers' skills are not a main additional source of estimation bias. In turn, we are well aware that unobserved firm characteristics are highly correlated with the wage offered, but including firm fixed effects is unfeasible as it implies dropping too many observations from a relatively small sample. If larger companies are more likely to advertise low-carbon ads and have market power so pay higher wages on average, the low-carbon premium is an upper bound. Vice versa, the low-carbon premium is an lower bound if green companies are smaller than non-green companies. While there is some evidence that wind and solar generation is concentrated in small and medium sized establishments Popp et al. (2020*b*), it is not enough to argue that our estimates of the low-carbon wage premium are downwardly biased.

6.2 Results

Figure 5 reports the low-carbon wage premium for the eight occupational groups in the first and last period. To preserve sample size, we report in the main text the results of a parsimonious specification with only commuting zone fixed effects, job ad length (a proxy of task complexity) fixed effects, SOC 6-digit and year dummies. In the Appendix, we show that results are similar in richer specifications and estimating the yearly low-carbon wage premium. Three clear patterns emerge for all occupations. The first pattern is that, with the exception of architects (17-1), there is a positive and significant wage premium for low-carbon tasks in the initial period. The premium is very large and well above 10% for technicians and transport workers. Previous evidence highlight the importance of mid-level technical skills for the green transition (Marin and Vona, 2019; Vona et al., 2018). The low-carbon premium is relatively high for installation workers and physical scientists (around 7%). Importantly, installation workers and technicians are also the two groups for which we observe the largest skill gaps. The green wage premium for business specialists is also around 5%, possibly reflecting the difficulties to fill the gap in technical skills in such profession. The low-carbon wage premium is significantly modest (2.6%) and only significant at 10% level for engineers. Finally, job offers for low-carbon construction workers are higher than those for other workers in the same group, but the estimated coefficient is far from being statistically significant at conventional levels. The small number of low carbon jobs in architecture means results may be spurious.

The second pattern is the widespread and pronounced decline of the low-carbon premia in the most recent years. The low-carbon premia becomes negative for scientists and engineers. The low-carbon offers for engineers are significantly lower than the average (-4.5%). Analogously, a large decline is observed for technicians that, however, maintains a positive and significant low-carbon premium in second period (+4.2%). The decline for business specialists is also enough to eliminate the low-carbon premium.[5] In green construction jobs, wage offers exhibit a sharp drop that makes the low-carbon wage premium negative at conventional levels of statistical significance (-2.1%). Installation, maintenance and repairer workers engaged in low-carbon activities experience a more modest reductions in the plausible range of wage offers. This finding is consistent with the fact that repairing and maintenance tasks are in high demand after construction activities are completed. Low carbon architect wages buck the trend with an improvement in relative wages but this again may be spurious. Note again that the low-carbon wage premium remains positive and statistically significant only in the two occupations in which skill gaps where largest. This suggests that US labor markets correctly signal potential reskilling needs in these two occupations.

Last, this declining pattern is less pronounced in high-carbon ads. We document this in the Appendix by applying the same regression model used here. For both construction and engineering jobs, the high-carbon premium is above 20% so significantly higher than the wage offers for low-carbon ads in similar occupations. Even if the high-carbon premium declined in both cases, it remains around 8% for engineers and 16% for extraction workers (compared to their relative reference group: other engineers and other construction workers). This finding raises two types of concerns. First, highly talented engineers may still be more attracted by a job in fossil-fuel industries than by a job in low-carbon sectors, reducing the innovative capacity to tackle climate change problems. Second, extraction workers displaced by climate policies or

[5] However, this is the only case where robustness analyses in the Appendix shows a different, slightly increasing pattern.

future green deal plans may possess a set of skill suitable for low-carbon activities, but much lower wage rates will make them less satisfied in the new job and thus more willing to oppose the approval of ambitious climate policies.

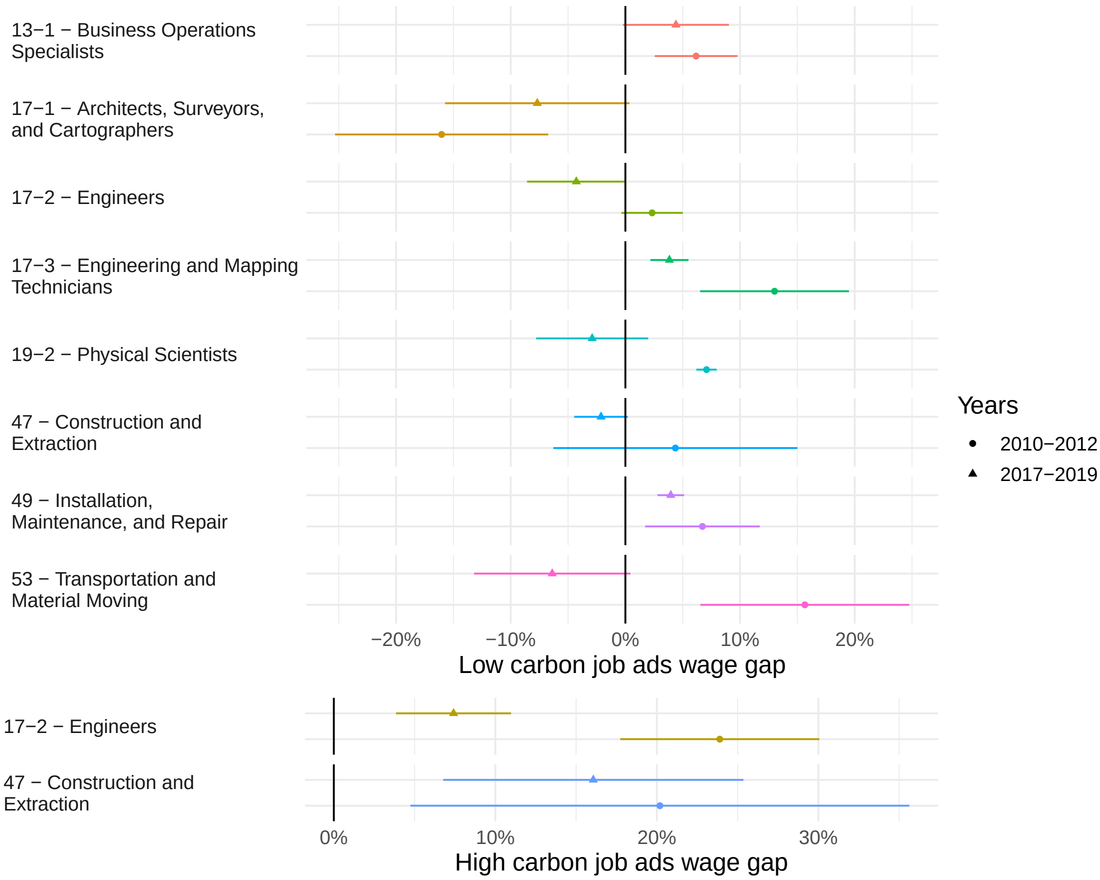

Figure 5: Wage gap between low, high carbon and generic job ads by period

Notes: The logarithm of annual wage reported in a job ad is regressed on indicator of whether the ad is low (resp. high) carbon while controlling for time dummies, 6-digits SOC occupation code dummies, commuting zone dummies and 2-digits NAICS industry dummies. Wage and NAICS codes are simultaneously observed in 9% of the ads for the 6 occupations listed, 3.2% of which are low carbon.

Discussion

Inspired by the task-based approach to labour markets, this paper shows how job vacancy data can be used to study labour market consequences of the low carbon transition. A key novelty of our study is the use of a bag of words model as in Atalay et al. (Forthcoming), but augmented with expert elicitation to solve well-known ambiguities in building a taxonomy of low-carbon activities. This method allows to identify low-carbon jobs, thus assessing emerging skill and wage gaps in very specific occupations and technological domains. At the macro-level, large scale mobilisation of the workforce in the low carbon transition is expected over the next decades, if countries were to meet pledged targets of massive GHGs reduction (relative to 2005) by 2030 and net zero by 2050.[6]. The job reallocation involved in ambitious decarbonization scenarios can be massive (Castellanos and Heutel, 2019; Hafstead and Williams III, 2018), but policymakers and modelers lack the adequate toolkit to examine the reallocation costs associated with job-to-job transitions. Our method can help modelers estimating reallocation costs by using skill gaps at a very granular level of occupational aggregation. Likewise, the approach proposed in this paper can be used by policymakers to track skill gaps in real time using local repositories of job ads (which are available in languages other than English), thus improving the effectiveness of retraining programs for low-carbon jobs.

The backdrop of our study is that of a very modest effort for decarbonization, with US Greenhouse Gas emissions falling by only 6.2% during our sample period. Still, we observe some interesting patterns that can inform deep decarbonization scenarios. Notably, low-carbon jobs are more skill-intensive than other similar ads, although they do not necessarily pay higher wages. While technical skills appear particularly important for low-carbon job ads in all occupations, reskilling paths appear heterogeneous across occupations. In some occupations, such as managers, low-carbon tasks require a reorientation of the skill set away from the core. In other occupations, such as engineering occupations, low-carbon jobs require a further specialization in the core set of skills. Finally, other occupational groups, such as technicians and installation workers, exhibits no clear pattern, suggesting the need of cooperation among social actors to find the appropriate solutions.

Because demand for low-carbon activities is primarily driven by policy, the widespread decline in green wage premia across all occupations resonates with the sudden boom and bust in US climate policy over the last decade. The decline of the green wage premia raises concerns for the attractiveness of high-tech green activities for the most talented scientists and engineers. While the extent of the pass-through of green subsidies to workers deserve further investigations, a suggestive interpretation of our results is that market signals alone may still not suffice in providing the right incentives to invest in low-carbon skills or to attract the best talents in innovative green sectors. A great deal of coordination among policy actors may be needed to overcome market failures in training and allocation of talents along the transition path. The

[6]https://cfpub.epa.gov/ghgdata/inventoryexplorer/allsectors/allsectors/allgas/econsect/all

policy landscape is clearly open to innovation, but hybrid forms of cooperation among different economic actors, such as those adopted in Scandinavian and German-speaking countries, appear particularly suitable when skill gaps are highly specific to particular technologies and locations (Hall and Soskice, 2001).

An aspect of labour markets for low-carbon activities that may be particularly difficult to manage is the gap between higher skill requirements and lack of wage premia that compensate for human capital investments. Such gap is particularly striking when using high-carbon ads as a comparison group. Although sharing a similar set of skills, high-carbon activities still offer much higher wages than low-carbon ones. A misallocation of talents towards the wrong technological trajectory can be the likely outcome of this persistent pay. This aspect of the labour market adjustments compounds with the high spatial concentration of fossil fuel activities by creating additional barriers to achieve a just transition. Ironically, high-carbon jobs are well-paid in relatively poorer locations, which contributes to explain the political opposition against ambitious climate policies of such regions (Tomer, Kane and George, 2021; Weber, 2020).

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A Identifying low carbon jobs

A.1 Expert survey email

Dear [Expert],

With [coauthor] and [coauthor], I am currently working on a project to identify the competencies necessary in the transition to a zero-carbon economy from an exhaustive dataset of all online job vacancies in the US over the past decade.

One major step involves the definition of what is a low carbon job vacancy among millions of possible job vacancies. We have applied Natural Language Processing techniques to automate the selection of low carbon job vacancies starting from a predefined set of clean energy keywords from previous research on the topic. By "low carbon" we mean an activity that reduces GHG emissions in several sectors: agriculture and forestry; power generation, storage and distribution; energy efficiency; manufacturing; transport; building and construction; engineering; research, design & consulting; regulation.

However, we need an expert review for a subset of identifiers that are ranked by the algorithm as "low carbon", but only marginally so.

Would you be willing to review the attached list of 125 attributes of a job vacancy and label those you consider to be "low carbon" according to your own expert knowledge?

Many thanks for your help!

Kind regards,

A.2 Example of low carbon ads

Table A1: 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
Driver	53-3032 - Heavy and Tractor-Trailer Truck Drivers	Sterling Heights, Michigan	High School	120k - 120k	**Bus Driving**, Over The Road, Repair, Truck Driving

A.3 Job identifiers and keywords

Table A2: Top 50 low carbon identifiers most commonly observed in job ads

Low carbon identifier	Ad count	Low carbon identifier	Ad count
Bus Driving	210,459	Efficient Transportation	21,115
Insulation	177,865	Public Transit Systems	20,825
Energy Efficiency	156,830	Emissions Testing	20,335
Energy Conservation	128,151	Pollution Control	20,247
Renewable Energy	127,146	Fuel Cell	19,596
Retrofitting	89,088	Electric Vehicle	19,281
Solar Energy	58,834	Energy Reduction	18,412
Climate Change	43,228	Insulation Installation	18,066
Clean Energy	37,395	Alternative Fuels	16,793
Solar Sales	36,795	Clean Air Act	16,546
Pollution Prevention	32,959	Geothermal	16,480
Environmental Sustainability	32,856	Greenhouse Gas	15,521
Air Emissions	31,452	Solar Installation	14,725
Wind Power	31,272	Federal Railroad Administration	14,647
Wind Turbines	29,202	Sustainable Energy	13,922
Photovoltaic (PV) Systems	26,249	Green Energy	13,462
Alternative Energy	25,997	Energy Conservation Measures	13,200
Smart Grid	25,725	Solar Systems	12,980
Sustainable Design	24,826	Weatherization	12,842
Fuel Efficiency	24,550	Air Permitting	12,750
Solar Panels	24,316	Biomass	12,081
Air Pollution Control	24,184	Energy Policy	11,558
Ethanol	23,026	Solar Consultation	10,630
Light Rail	21,560	Clean Technology	10,466
Green Building	21,442	Emissions Management	10,092

B Descriptive statistics

B.1 Representativeness of BG data

Table B1: Share of low carbon ads by SOC major group (2-digits), weighted by BLS employment

SOC major group	Low carbon ads	Share within occupation
11 - Management	256,515	1.3%
13 - Business and Financial Operations	95,727	1.7%
15 - Computer and Mathematical	121,578	0.6%
17 - Architecture and Engineering	233,436	4.1%
19 - Life, Physical, and Social Science	50,355	3.6%
21 - Community and Social Service	5,083	0.3%
23 - Legal	9,033	0.6%
25 - Education, Training, and Library	31,610	0.6%
27 - Arts, Design, Entertainment, Sports, and Media	21,404	0.5%
29 - Healthcare Practitioners and Technical	34,293	0.1%
31 - Healthcare Support	9,363	0.2%
33 - Protective Service	18,720	1.0%
35 - Food Preparation and Serving Related	13,797	0.2%
37 - Building and Grounds Cleaning and Maintenance	13,107	0.5%
39 - Personal Care and Service	12,284	0.3%
41 - Sales and Related	142,877	0.4%
43 - Office and Administrative Support	90,492	0.4%
45 - Farming, Fishing, and Forestry	913	0.9%
47 - Construction and Extraction	94,725	4.1%
49 - Installation, Maintenance, and Repair	170,476	2.6%
51 - Production	46,594	0.9%
53 - Transportation and Material Moving	201,263	7.4%
Total	1,673,645	1.4%

B.2 Low carbon ads statistics

Table B2: 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	78,545	2.5%
13-2 - Financial Specialists	17,182	0.4%
17-1 - Architects, Surveyors, and Cartographers	10,473	4.3%
17-2 - Engineers	180,294	4.3%
17-3 - Engineering and Mapping Technicians	42,669	3.5%
19-1 - Life Scientists	10,379	2.3%
19-2 - Physical Scientists	20,064	8.0%
19-3 - Social Scientists and Related Workers	8,588	2.3%
19-4 - Life, Physical, and Social Science Technicians	11,324	2.1%
Total	1,673,645	1.4%

Table B3: Representativeness of Burning Glass ads dataset vs. BLS employment

SOC major group	Ad count	Unweighted ad share	BLS employment share
11 - Management	22,716,404	12.0%	5.0%
13 - Business and Financial Operations	13,035,329	6.9%	5.1%
15 - Computer and Mathematical	22,438,181	11.9%	2.9%
17 - Architecture and Engineering	6,073,207	3.2%	1.8%
19 - Life, Physical, and Social Science	1,946,038	1.0%	0.8%
21 - Community and Social Service	2,178,888	1.2%	1.4%
23 - Legal	1,572,981	0.8%	0.8%
25 - Education, Training, and Library	5,119,425	2.7%	5.8%
27 - Arts, Design, Entertainment, Sports, and Media	4,629,983	2.5%	1.3%
29 - Healthcare Practitioners and Technical	23,327,278	12.4%	5.9%
31 - Healthcare Support	4,025,828	2.1%	2.9%
33 - Protective Service	2,016,089	1.1%	2.5%
35 - Food Preparation and Serving Related	6,985,491	3.7%	9.1%
37 - Building and Grounds Cleaning and Maintenance	2,441,462	1.3%	3.2%
39 - Personal Care and Service	3,691,927	2.0%	3.1%
41 - Sales and Related	22,709,208	12.0%	10.6%
43 - Office and Administrative Support	19,903,972	10.5%	16.1%
45 - Farming, Fishing, and Forestry	126,592	0.1%	0.3%
47 - Construction and Extraction	1,998,832	1.1%	3.9%
49 - Installation, Maintenance, and Repair	5,909,063	3.1%	3.9%
51 - Production	4,897,885	2.6%	6.6%
53 - Transportation and Material Moving	10,994,453	5.8%	6.9%

Table B4: 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	1.32%	1.42%	1.44%	1.30%	1.20%	1.34%	1.28%	1.39%	1.40%	1.42%
Overall - High skill										
All	0.36%	0.41%	0.37%	0.30%	0.30%	0.32%	0.29%	0.29%	0.30%	0.30%
13-1 - Business Operations Specialists	0.09%	0.13%	0.10%	0.07%	0.07%	0.07%	0.07%	0.06%	0.07%	0.06%
17-2 - Engineers	0.06%	0.07%	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	0.18%	0.20%	0.20%	0.16%	0.17%	0.18%	0.16%	0.16%	0.17%	0.17%
Overall - Low skill										
All	0.97%	1.01%	1.06%	1.00%	0.90%	1.02%	0.98%	1.10%	1.10%	1.12%
47 - Construction and Extraction	0.14%	0.15%	0.14%	0.14%	0.15%	0.19%	0.18%	0.19%	0.18%	0.18%
49 - Installation, Maintenance, and Repair	0.08%	0.09%	0.09%	0.10%	0.08%	0.10%	0.10%	0.12%	0.12%	0.12%
53 - Transportation and Material Moving	0.54%	0.51%	0.54%	0.53%	0.44%	0.47%	0.47%	0.53%	0.54%	0.55%
Others	0.21%	0.26%	0.30%	0.23%	0.23%	0.26%	0.24%	0.26%	0.26%	0.27%
Within occupation group										
13-1 - Business Operations Specialists	2.95%	4.00%	3.22%	2.24%	2.08%	2.32%	2.05%	1.94%	2.06%	1.90%
17-1 - Architects, Surveyors, and Cartographers	3.30%	4.15%	3.20%	2.84%	5.81%	7.31%	4.75%	3.42%	3.99%	4.20%
17-2 - Engineers	5.19%	5.60%	4.63%	3.92%	3.85%	4.05%	3.97%	3.94%	3.87%	3.89%
17-3 - Engineering and Mapping Technicians	3.68%	4.11%	3.30%	3.09%	3.53%	3.34%	3.43%	3.65%	3.45%	3.61%
19-2 - Physical Scientists	8.15%	8.95%	8.12%	7.73%	7.86%	8.75%	7.14%	7.33%	8.52%	7.85%
47 - Construction and Extraction	3.52%	3.72%	3.62%	3.45%	3.70%	4.77%	4.62%	4.96%	4.48%	4.56%
49 - Installation, Maintenance, and Repair	2.01%	2.42%	2.24%	2.64%	2.18%	2.61%	2.50%	3.04%	3.05%	3.09%
53 - Transportation and Material Moving	7.78%	7.44%	7.80%	7.65%	6.43%	6.88%	6.78%	7.73%	7.83%	8.00%

C Spatial correlation between low and high carbon vacancies and income levels

Table C1: Correlation between the share of low carbon ads and annual personal income

	Low skill			High skill		
	Unweighted	Weighted by ad count	Weighted by population	Unweighted	Weighted by ad count	Weighted by population
log(income)	0.006***	0.002*	0.002**	0.006***	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Observations	685	685	685	676	676	676
R2	0.03	0.01	0.02	0.05	0.05	0.06
AIC	−4.974	−4.960	−4.961	−5.257	−5.251	−5.250

Table C2: Correlation between the share of high carbon ads and annual personal income

	Low skill			High skill		
	Unweighted	Weighted by ad count	Weighted by population	Unweighted	Weighted by ad count	Weighted by population
log(income)	0.007***	−0.001**	−0.001***	0.003*	−0.001	0.000
	(0.002)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Observations	647	647	647	569	569	569
R2	0.03	0.01	0.01	0.01	0.00	0.00
AIC	−4.522	−4.456	−4.459	−4.306	−4.259	−4.267

Table C3: Correlation between the share of low and high carbon ads

	Low skill			High skill		
	Unweighted	Weighted by ad count	Weighted by population	Unweighted	Weighted by ad count	Weighted by population
log(1 + s_{hc}	0.122**	0.065	0.067	0.073*	0.198***	0.208***
	(0.057)	(0.045)	(0.052)	(0.038)	(0.051)	(0.052)
Observations	650	650	646	569	569	566
R2	0.02	0.00	0.00	0.01	0.03	0.04
AIC	−4.760	−4.757	−4.728	−4.491	−4.457	−4.445

Table C4: Locational Gini

	Low carbon ads	High carbon employment	High carbon ads		Generic ads
Low skill	0.17	0.45	0.34	Construction & Extraction	0.12
High skill	0.16	0.48	0.40	Engineers	0.17

D Broad skill gap

Table D1: Keywords defining broad skills

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

Table D2: Skill gap

	Cognitive		IT		Technical		Management		Social	
	1	2+	1	2+	1	2+	1	2+	1	2+
13-1 - Business Operations Specialists										
Generic	25.2%	9.9%	21.1%	28.7%	26.0%	22.4%	28.0%	28.2%	16.2%	2.1%
Low carbon	26.3%	10.9%	20.7%	27.4%	26.3%	28.7%	27.9%	33.7%	21.2%	8.8%
17-1 - Architects, Surveyors, and Cartographers										
Generic	18.1%	3.9%	15.9%	24.3%	24.9%	14.9%	25.6%	18.5%	16.9%	7.3%
Low carbon	22.7%	10.5%	28.1%	16.1%	31.4%	26.5%	28.6%	32.4%	27.3%	16.0%
17-2 - Engineers										
Generic	25.2%	7.2%	19.7%	26.8%	24.3%	13.8%	26.0%	20.0%	25.6%	20.1%
High carbon	23.7%	5.5%	21.3%	15.9%	28.1%	13.8%	29.0%	19.6%	26.7%	22.3%
Low carbon	26.9%	7.8%	22.7%	25.0%	29.9%	21.4%	31.0%	25.0%	29.7%	28.3%
17-3 - Engineering and Mapping Technicians										
Generic	16.6%	3.1%	15.4%	16.4%	13.7%	5.4%	20.3%	11.7%	19.5%	9.0%
Low carbon	20.6%	4.5%	18.7%	21.1%	23.9%	11.9%	28.9%	18.9%	28.2%	16.2%
19-2 - Physical Scientists										
Generic	33.5%	16.9%	15.6%	11.5%	19.9%	10.1%	25.0%	21.1%	15.4%	3.3%
Low carbon	35.9%	12.6%	17.9%	19.0%	26.1%	29.8%	27.0%	27.3%	22.1%	7.6%
47 - Construction and Extraction										
Generic	6.3%	1.2%	5.2%	2.5%	8.2%	3.0%	11.4%	4.2%	12.3%	3.1%
High carbon	14.3%	1.6%	10.9%	12.2%	10.7%	4.4%	19.7%	8.6%	14.1%	3.1%
Low carbon	9.9%	1.6%	10.9%	3.9%	14.6%	5.0%	15.0%	11.8%	13.6%	5.2%
49 - Installation, Maintenance, and Repair										
Generic	12.3%	1.8%	9.1%	7.3%	13.0%	6.5%	20.5%	9.5%	13.2%	3.3%
Low carbon	11.6%	2.3%	12.2%	8.6%	24.4%	8.3%	28.6%	14.4%	24.6%	5.4%
53 - Transportation and Material Moving										
Generic	5.2%	0.4%	2.8%	1.1%	4.7%	1.4%	7.5%	2.7%	1.7%	0.1%
Low carbon	5.1%	0.5%	2.7%	1.2%	4.9%	1.5%	14.4%	5.2%	4.6%	0.2%

Figure D1: Differences in broad skills, ads comprising 1 to 8 skills

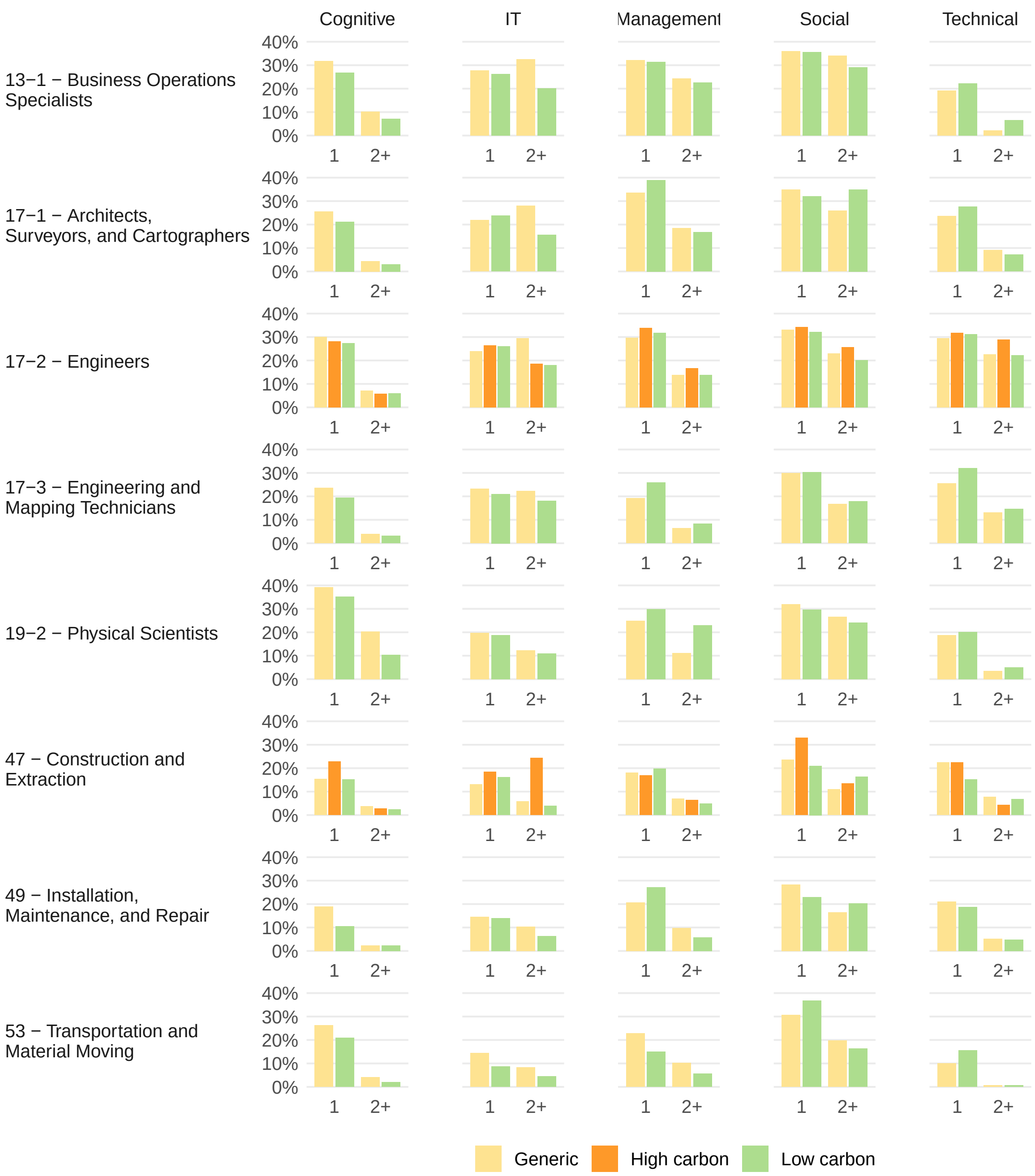

Figure D2: Differences in broad skills, ads comprising 9 to 16 skills

Figure D3: Differences in broad skills, ads comprising more than 17 skills

E Wage gap

Table E1: Wage gap robustness (Main specification)

	Main specification			
	Weighted		Unweighted	
	2010-2012	2017-2019	2010-2012	2017-2019
13-1 - Business Operations Specialists				
Job ad is low carbon	0.062***	0.044*	0.063***	0.034
	(0.017)	(0.022)	(0.019)	(0.020)
Total ads	237,257	716,067	237,257	716,067
Low carbon ads	3,048	7,855	3,048	7,855
R2	0.204	0.218	0.195	0.209
17-1 - Architects, Surveyors, and Cartographers				
Job ad is low carbon	-0.241***	-0.087*	-0.247***	-0.101
	(0.021)	(0.035)	(0.013)	(0.050)
Total ads	6,122	18,958	6,122	18,958
Low carbon ads	238	678	238	678
R2	0.355	0.216	0.394	0.254
17-2 - Engineers				
Job ad is low carbon	0.023*	-0.043*	0.017	-0.038
	(0.013)	(0.020)	(0.013)	(0.025)
Total ads	138,328	205,682	138,328	205,682
Low carbon ads	7,287	10,057	7,287	10,057
R2	0.137	0.104	0.143	0.106
17-3 - Engineering and Mapping Technicians				
Job ad is low carbon	0.130***	0.038***	0.109***	0.041***
	(0.030)	(0.008)	(0.022)	(0.010)
Total ads	83,875	199,662	83,875	199,662
Low carbon ads	1,732	3,745	1,732	3,745
R2	0.185	0.140	0.204	0.159
19-2 - Physical Scientists				
Job ad is low carbon	0.071***	-0.029	0.071***	-0.011
	(0.004)	(0.021)	(0.008)	(0.038)
Total ads	16,775	25,707	16,775	25,707
Low carbon ads	1,151	2,473	1,151	2,473
R2	0.249	0.191	0.254	0.213
47 - Construction and Extraction				
Job ad is low carbon	0.044	-0.021*	0.040	-0.014
	(0.053)	(0.012)	(0.038)	(0.011)
Total ads	98,200	269,768	98,200	269,768
Low carbon ads	3,976	13,261	3,976	13,261
R2	0.267	0.291	0.256	0.264
49 - Installation, Maintenance, and Repair				
Job ad is low carbon	0.067***	0.040***	0.050*	0.035***
	(0.025)	(0.006)	(0.030)	(0.009)
Total ads	213,923	567,184	213,923	567,184
Low carbon ads	5,757	15,376	5,757	15,376
R2	0.149	0.133	0.172	0.163
53 - Transportation and Material Moving				
Job ad is low carbon	0.157***	-0.064*	0.108*	-0.030
	(0.045)	(0.034)	(0.063)	(0.037)
Total ads	349,336	1,489,698	349,336	1,489,698
Low carbon ads	10,155	35,860	10,155	35,860
R2	0.359	0.394	0.341	0.388
Fixed effects				
Year	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes
6-digits SOC	Yes	Yes	Yes	Yes
Degree	No	No	No	No

Table E2: Wage gap robustness (Control for degree)

	Control for degree			
	Weighted		Unweighted	
	2010-2012	2017-2019	2010-2012	2017-2019
13-1 - Business Operations Specialists				
Job ad is low carbon	0.027	0.047**	0.026	0.042**
	(0.026)	(0.017)	(0.023)	(0.015)
Total ads	123,559	429,527	123,559	429,527
Low carbon ads	1,735	4,273	1,735	4,273
R2	0.255	0.267	0.250	0.265
17-1 - Architects, Surveyors, and Cartographers				
Job ad is low carbon	-0.185***	-0.093***	-0.188***	-0.094**
	(0.022)	(0.014)	(0.005)	(0.020)
Total ads	2,714	10,815	2,714	10,815
Low carbon ads	161	483	161	483
R2	0.414	0.250	0.468	0.304
17-2 - Engineers				
Job ad is low carbon	0.030*	-0.013**	0.019	-0.006
	(0.017)	(0.005)	(0.016)	(0.009)
Total ads	91,005	149,391	91,005	149,391
Low carbon ads	5,556	7,614	5,556	7,614
R2	0.102	0.112	0.108	0.112
17-3 - Engineering and Mapping Technicians				
Job ad is low carbon	0.104**	0.031	0.079***	0.031
	(0.038)	(0.020)	(0.025)	(0.019)
Total ads	39,976	104,238	39,976	104,238
Low carbon ads	1,034	2,337	1,034	2,337
R2	0.312	0.231	0.335	0.258
19-2 - Physical Scientists				
Job ad is low carbon	0.048	0.006	0.050**	0.014
	(0.027)	(0.016)	(0.020)	(0.026)
Total ads	10,994	18,955	10,994	18,955
Low carbon ads	836	1,909	836	1,909
R2	0.265	0.230	0.272	0.252
47 - Construction and Extraction				
Job ad is low carbon	-0.013	-0.002	0.011	0.006
	(0.029)	(0.018)	(0.025)	(0.017)
Total ads	22,389	65,878	22,389	65,878
Low carbon ads	1,263	4,347	1,263	4,347
R2	0.359	0.419	0.349	0.386
49 - Installation, Maintenance, and Repair				
Job ad is low carbon	0.085***	0.042***	0.067**	0.043***
	(0.019)	(0.005)	(0.029)	(0.009)
Total ads	73,780	235,624	73,780	235,624
Low carbon ads	2,411	6,651	2,411	6,651
R2	0.263	0.202	0.284	0.237
53 - Transportation and Material Moving				
Job ad is low carbon	-0.044	0.202***	-0.033	0.154***
	(0.078)	(0.015)	(0.033)	(0.038)
Total ads	74,384	282,924	74,384	282,924
Low carbon ads	4,149	17,915	4,149	17,915
R2	0.261	0.288	0.334	0.299
Fixed effects				
Year	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes
6-digits SOC	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes

Table E3: Wage gap robustness (Control for industry)

	Control for industry			
	Weighted		Unweighted	
	2010-2012	2017-2019	2010-2012	2017-2019
13-1 - Business Operations Specialists				
Job ad is low carbon	0.027	0.047**	0.026	0.042**
	(0.026)	(0.017)	(0.023)	(0.015)
Total ads	123,559	429,527	123,559	429,527
Low carbon ads	1,735	4,273	1,735	4,273
R2	0.255	0.267	0.250	0.265
17-1 - Architects, Surveyors, and Cartographers				
Job ad is low carbon	-0.185***	-0.093***	-0.188***	-0.094**
	(0.022)	(0.014)	(0.005)	(0.020)
Total ads	2,714	10,815	2,714	10,815
Low carbon ads	161	483	161	483
R2	0.414	0.250	0.468	0.304
17-2 - Engineers				
Job ad is low carbon	0.030*	-0.013**	0.019	-0.006
	(0.017)	(0.005)	(0.016)	(0.009)
Total ads	91,005	149,391	91,005	149,391
Low carbon ads	5,556	7,614	5,556	7,614
R2	0.102	0.112	0.108	0.112
17-3 - Engineering and Mapping Technicians				
Job ad is low carbon	0.104**	0.031	0.079***	0.031
	(0.038)	(0.020)	(0.025)	(0.019)
Total ads	39,976	104,238	39,976	104,238
Low carbon ads	1,034	2,337	1,034	2,337
R2	0.312	0.231	0.335	0.258
19-2 - Physical Scientists				
Job ad is low carbon	0.048	0.006	0.050**	0.014
	(0.027)	(0.016)	(0.020)	(0.026)
Total ads	10,994	18,955	10,994	18,955
Low carbon ads	836	1,909	836	1,909
R2	0.265	0.230	0.272	0.252
47 - Construction and Extraction				
Job ad is low carbon	-0.013	-0.002	0.011	0.006
	(0.029)	(0.018)	(0.025)	(0.017)
Total ads	22,389	65,878	22,389	65,878
Low carbon ads	1,263	4,347	1,263	4,347
R2	0.359	0.419	0.349	0.386
49 - Installation, Maintenance, and Repair				
Job ad is low carbon	0.085***	0.042***	0.067**	0.043***
	(0.019)	(0.005)	(0.029)	(0.009)
Total ads	73,780	235,624	73,780	235,624
Low carbon ads	2,411	6,651	2,411	6,651
R2	0.263	0.202	0.284	0.237
53 - Transportation and Material Moving				
Job ad is low carbon	-0.044	0.202***	-0.033	0.154***
	(0.078)	(0.015)	(0.033)	(0.038)
Total ads	74,384	282,924	74,384	282,924
Low carbon ads	4,149	17,915	4,149	17,915
R2	0.261	0.288	0.334	0.299
Fixed effects				
Year	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes
6-digits SOC	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes

Table E4: Wage sample balance (full sample)

	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	8,049,595	11.2	7.6	13.6	5.2	3.8	2.6	51,907	28,456
Low carbon	78,518	14.7	8.5	13.9	5.0	4.2	2.9	56,544	28,608
17-2 - Engineers									
Generic	3,622,206	11.5	7.6	15.1	4.0	5.1	3.1	69,908	29,486
High carbon	99,572	10.2	6.7	15.6	2.7	6.0	3.5	91,247	46,603
Low carbon	180,262	16.0	8.5	15.3	3.7	5.3	3.2	68,407	25,775
17-3 - Engineering and Mapping Technicians									
Generic	1,897,103	9.0	6.9	11.5	5.1	3.7	2.7	40,981	20,903
Low carbon	42,653	14.3	8.1	12.6	4.4	4.3	2.9	46,951	21,085
19-2 - Physical Scientists									
Generic	343,905	10.7	6.8	16.1	3.9	4.3	3.2	57,392	31,584
Low carbon	20,059	15.5	8.5	16.0	3.9	4.4	3.2	55,245	23,128
47 - Construction and Extraction									
Generic	1,793,801	5.9	5.6	6.9	6.2	3.7	2.5	39,470	22,710
High carbon	110,232	7.5	6.2	10.9	4.8	3.1	2.6	43,132	25,198
Low carbon	94,710	10.0	7.3	8.3	5.9	3.4	2.4	42,603	24,160
49 - Installation, Maintenance, and Repair									
Generic	5,738,508	8.1	6.4	9.5	5.3	3.1	2.3	39,648	22,171
Low carbon	170,465	13.0	7.5	9.0	5.6	3.0	2.4	43,841	21,256

Table E5: Wage sample balance (subsample with salary information)

	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.	t-test
13-1 - Business Operations Specialists													
Generic	1,430,951	10.3	7.2	-0.849***	12.2	6.4	-1.42***	3.2	2.4	-0.574***	51,907	28,456	3.64e-11
Low carbon	16,915	14.0	8.7	-0.699***	11.9	6.8	-1.95***	3.3	2.6	-0.893***	56,544	28,608	4.37e-11
17-2 - Engineers													
Generic	521,104	10.8	7.5	-0.637***	14.7	4.5	-0.41***	4.5	3.0	-0.689***	69,908	29,486	0
High carbon	7,548	8.7	6.9	-1.51***	15.1	3.9	-0.509***	6.0	3.6	-0.0536	91,247	46,603	-2.91e-11
Low carbon	27,409	16.2	9.3	0.167***	14.9	4.2	-0.373***	4.3	3.2	-0.967***	68,407	25,775	-1.46e-11
17-3 - Engineering and Mapping Technicians													
Generic	435,558	8.3	6.5	-0.707***	10.2	5.8	-1.37***	3.1	2.5	-0.632***	40,981	20,903	7.28e-12
Low carbon	8,470	13.7	9.1	-0.583***	11.4	5.3	-1.24***	3.6	2.6	-0.743***	46,951	21,085	-1.46e-11
19-2 - Physical Scientists													
Generic	65,362	10.3	6.9	-0.371***	15.2	4.9	-0.889***	3.1	2.7	-1.2***	57,392	31,584	-2.18e-11
Low carbon	6,480	16.7	9.0	1.18***	15.2	4.8	-0.746***	3.1	2.5	-1.31***	55,245	23,128	4.37e-11
47 - Construction and Extraction													
Generic	530,065	5.8	5.5	-0.099***	5.6	6.2	-1.33***	3.5	2.4	-0.227***	39,470	22,710	1.46e-11
High carbon	14,620	6.0	5.6	-1.45***	8.6	6.1	-2.31***	3.2	2.6	0.15***	43,132	25,198	-2.18e-11
Low carbon	27,894	9.5	7.8	-0.483***	6.9	6.2	-1.35***	3.1	2.2	-0.261***	42,603	24,160	1.46e-11
49 - Installation, Maintenance, and Repair													
Generic	1,162,640	7.8	6.2	-0.311***	7.9	6.0	-1.6***	3.0	2.2	-0.091***	39,648	22,171	0
Low carbon	33,261	12.9	8.4	-0.173***	8.4	5.8	-0.624***	3.3	2.4	0.255***	43,841	21,256	7.28e-12