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

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Accurately identifying low-carbon jobs is central to understanding the labour market impacts of the low-carbon transition. We develop a novel methodology to identify low-carbon jobs using the near universe of online job postings between 2010-2019 in the US. The share of low-carbon ads in the US economy has been constant around 1.3%, but is growing slightly in low-skilled occupations. We compare low-carbon to other job ads within narrow occupational groups and show that the green skill gaps are larger and broader than previously considered. Emphasis on technical and managerial skills is a distinguishing characteristic of all low-carbon job ads, but skill requirements are higher in general, including in cognitive and IT skills that are also important for the digital transformation. Low-carbon job ads pay a significant wage premium, but such premium declined over time.

Reaching climate neutrality by mid-century requires a deep transformation of all economic sectors (*1*). In parallel with ongoing technological trends in digitization and Artificial Intelligence (*2,3*), 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 delivering jobs (*4*) and supporting a "just transition" that addresses the needs of workers and communities of high-carbon industries is a key priority to enhance the political acceptability of climate action (*5*) particularly in the postpandemic context (*6*).

Yet despite substantial recent progress, understanding the skill content and other characteristics of low-carbon jobs vis-à-vis high carbon or generic jobs remains a challenge, owing to the fundamental problem of identifying low-carbon jobs with precision. High carbon jobs linked to fossil fuels extraction and production are easily identified, but conceptual issues and data limitations make it significantly more difficult to define the jobs that will benefit from ambitious climate policies, such as green deal plans. The transition will create some new occupations for example in renewable energy, but in the majority of cases, the greening of jobs is happening within established occupations. For example, more automobile engineers have to adapt to hybrid, electric or hydrogen technologies. Low-carbon jobs are often those whose content is altered with the adoption of new green technologies or of new green methods of production. But the difficulty of isolating greening jobs from similar non-green jobs in the same occupation has meant that the green jobs discourse has narrowly focused on segments of the green economy such as renewable energy or traditional environmental sectors like waste and water.

Because green jobs are more difficult to observe than brown jobs, public debate exaggerates the job killing argument while downplaying the job creation effect of the low-carbon transition. The evidence is largely silent on reallocation costs associated with workers' reskilling (*7*) and earning losses (*8*), which are often ignored when evaluating labour market impacts of environmental policies (*9–15*).

Advancing knowledge on green jobs, recent studies combine insights from the task-based approach to labour markets (*2, 3*) with occupation-level data on task and skill requirements from the Green Economy Program of the Occupational information network (O*NET) (*7, 16–19*) to measure occupation level exposure to green technologies and productions. Using this approach (*7*) shows that greener occupations rely heavily on technical and engineering skills to solve and implement solutions to specific environmental problems. Still, O*NET lacks granularity, making it ill suited for characterising emerging low-carbon jobs compared to similar jobs within the same occupation.

To overcome limitations of occupation level analyses, this study develops a new three step procedure using job ad data to identify low-carbon jobs (full details are available in the Online Methods section). Following the recent literature on labour market adjustments to technological change (*20–24*), we use the comprehensive online job vacancy data from Emsi Burning Glass (hereafter, EmsiBG) covering the near-universe of online job vacancies posted in the US between 2010 and 2019. Job ads contain rich textual information on the skill requirements of jobs. EmsiBG cleans and codifies raw text from ads into a taxonomy of over 16,000 skills but these skills are not specifically labeled as green or non-green.

In a first step, drawing from (*25*), we select a set of valid tokenized low-carbon keywords from existing definitions of green tasks (from O*NET) and green products (from EU PRODCOM), then apply an unsupervised natural language processing algorithm to compute a score indicating how relevant each word is to low-carbon tasks and products. This results in a list of 250 low-carbon keywords. Second, we map these keywords to the 16,059 unique skills present in the EmsiBG dataset, using a natural language processing technique Word2Vec (*26*) that assigns a "low-carbon matching score" for every skill. This unsupervised portion of our classification algorithm excludes 15,063 potential identifiers that match none of our low-carbon keywords and leaving 600 ambiguous matches. Last, we resolve ambiguous cases through expert elicitation. This three-steps procedure gives a list of 445 low-carbon skills that we use as low-carbon job identifiers. A vacancy posing is considered low-carbon if it contains at least one low-carbon job identifier. The list of low-carbon related skills is made available with this publication to advance research and analyses in this area.

Taking advantage of the high density of low-carbon job ads in particular occupations, our approach allows us to reveal precisely how low-carbon jobs compare in terms of geographical distribution, skill requirements and wages vis-à-vis fossil fuel or similar jobs within occupational groups, such as engineers or construction workers. In doing so, we provide a very accurate characterisation of the potential skill gaps and hiring difficulties emerging in specific labour markets concerned by the low-carbon transition. The methodology is transparent and flexible, and can be easily replicated in different country contexts, offering a toolkit for policymakers to design targeted retraining and reskilling policies in green deal packages. The adaptability is key given the nature of green jobs is likely to continue to change through the diffusion of green technology in the economy as the low carbon transition advances.

Results

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. Low-carbon vacancy shares have remained stable at around 1.35 percent of total online job vacancies over the last decade (Figure 1). A mild increase was observed in the first three years (from 1.32% to 1.44%) coinciding with the job creation effect of the American Recovery and Reinvestment Act (ARRA) which devoted substantial funds to the low-carbon transition (*27, 28*). This is followed by a decline below 1.3% in the central period and another increase from 2017 onwards.

Importantly, job ad shares captures the flow of labour demand rather than the stock of workers in low-carbon positions. To improve representativeness, low carbon job ads are re-weighted using BLS employment shares (See section and Table 6). This approach produces estimates that are consistent with previous measures of green employment shares (*19*).

Figures 1A also shows that the decennial trends are divergent between high- skilled occupations (such as managers or engineers) that decline from 0.36% to 0.30%, and low-skill occupations (such as manual workers) that grow from 0.97% to 1.12% (see also Table 11 in the Appendix). The latter resonates with the job creation effect of green ARRA spending that was concentrated in manual occupations (*28*), and suggests that green recovery plans may potentially help to offset secular deterioration of the labour market conditions for unskilled workers. The emerging patters are rather small in absolute terms but statistically significant (see Table 13 in the Appendix).

To assess which sectors and occupations post low-carbon ads most intensively, we compare the share of low-carbon ads over total ads in Table 12, Table 8 and Figure 8 in the Appendix respectively. With our broad definition, low-carbon jobs are found across most sectors, especially service sectors such as public transport and professional services. In terms of occupations, Six 2-digit SOC groups stand out: Business and Finance 3.6%; Architecture and Engineering 4.1%; Life, Physical and Social Science; Construction and Extraction 4.1%; Installation, Maintenance and Repair 2.6% and Transportation 7.3%. The latter is due to public transportation and bus driving being included in our list of low-carbon identifiers. Except for transport, these occupations are also the most green-task intensive using O*NET data (*19*).

A two-digit occupational grouping still does not suffice in accounting for heterogeneity in occupational greenness. Substantial variation in low-carbon intensity across occupations is observed even within each 2-digit group (Table 9 in the Appendix for details). To capture such heterogeneity, we focus on the five high-skilled occupations at the 3-digit SOC level that have a high share of low-carbon ads (Business Specialists, Architects, Engineers, Technicians, Physical Scientists). For low-skilled occupations, we consider three 2-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 remaining panels of Figure 1B further documents varying trends across the eight key low-carbon intensive occupations that are the focus of this study. The small decline in low-carbon intensity is statistically significant for Business Specialists (from 2.9% to 1.9%), Architects (from 5.4% to 4.6%) and Engineers (from 5.2% to 3.9%) but not for Technicians and Physical Scientists (See Table 14 in the Appendix). The increase in the low-carbon intensity of Construction (from 3.5% to 4.6%) and Installation jobs (from 2% to 3.1%) is statistically significant. The share of green Transportation jobs stays flat. The unweighted (dotted) share of low-carbon ads is smaller than the weighted for most occupations, particularly Physical Scientists, Business Specialists and Transportation workers but trends are quite smooth despite increased coverage of EmsiBG data over time.

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. The high skill group includes SOC codes from 11 to 29; the low skill group includes codes above 29. 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.

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

One of the key challenges in delivering a "just transition" is to ensure that displaced workers in energy or pollution intensive industries find new jobs with similar pay and working conditions, possibly in low-carbon activities. The location of low-carbon jobs is an important factor determining employment prospects and reallocation costs for workers in communities that are vulnerable in the face of declining fossil fuels.

Figure 2 contrasts the geographical distribution of low- and high-carbon jobs in the U.S. focusing on low-skilled (mostly manual) occupations for which ensuring a just transition is key to boosting the political acceptability of climate policy and neutralising the job killing arguments often used by fossil fuel lobbies and climate deniers (*5, 29*). In particular, Figure 2A reports the average share of low- and high-carbon ads in low-skilled occupations during the period 2010-2019 at the commuting zone level. As marked in hashed orange here and was previously documented (*28*), high carbon manual jobs are extremely spatially concentrated around centres of coal, crude oil, gas and shale oil & gas extraction including Wyoming, West Virginia, Oklahoma and Texas and the Appalachian region. The pattern is similar when using high carbon employment shares (Figure 2B): employment shares better capture jobs in constantly declining sectors/ regions like coal whereas job-ad shares better capture shale fields where there is still ongoing job creation. Borrowing from the literature on adverse deindustrialization shocks (*30,31*), the spatial concentration of fossil fuel activities amplifies the negative effects of climate policies on fossil fuel communities through negative multiplier effects.

We find limited overlap between locations of low-carbon job creation and where job destruction is more likely to be concentrated. Table 17 reports that the correlation between the shares of high- and low-carbon ads is 0.122 and statistically significant at conventional level, but it halves and becomes statistically insignificant when weighted it by local population levels. This spatial mismatch between low- and high-carbon activities implies higher reallocation costs than previously thought when focusing on renewable energy jobs only (*32*). The geographical distribution of low-carbon jobs, especially renewable energy ones, also partially reflect natural resource endowment and the share of green low-skilled jobs is higher in areas with high solar power potential (e.g. California and Nevada) and around the wind corridor from Minnesota to Texas.

Figure 2 also illustrates how low-carbon vacancies are more spread across space. Locational Gini coefficient estimates are twice as high for high-carbon (0.68) as it is for low-carbon ads (0.34) (Table 19). Studies where the sample is restricted to renewable energy generation report high degree of spatial concentration in green and low-carbon manual activities (*7, 28*), suggesting the spatial dispersion found here is driven by low-carbon jobs in areas such as buildings or transport. Low-carbon jobs in Michigan, for example, are driven by bus drivers (Table 1).

Finally, our results concur with previous evidence (***?***) that low-carbon transition has the potential to exacerbate existing regional inequalities, because high carbon jobs tend to cluster in poorer regions, whereas low-carbon vacancies tend to be in wealthier areas (a 1% increase in average per capita income is associated with an 0.2% increase in the low-carbon ad share and a 0.1% fall in high carbon ads (Tables 15 and 16).

The fact that low-skilled displaced workers in fossil fuel industries may face less promising employment opportunities in low-carbon jobs than previously thought does not necessarily undermine a "just transition". Such workers can find jobs in other sectors or jobs indirectly created by the low-carbon transition. Still, our descriptive evidence lends support to the widespread idea that distressed fossil-fuel communities may require targeted place based policies, including retraining and reskilling policies, to successfully accomplish such transition (*33*).

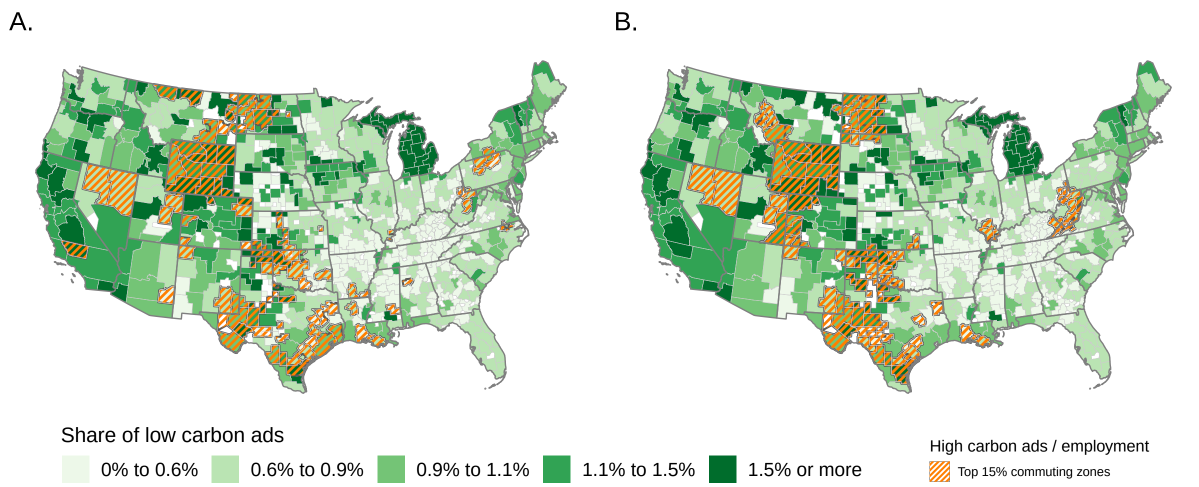

Figure 2: Spatial distribution of low-carbon vacancies and high carbon vacancies (A) and jobs (B) in low skilled occupations

Notes: low-carbon vacancies and high carbon vacancies and employment are presented for low-skilled occupations only (SOCs 31 to 53). 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 the commuting zones with a high share of high-carbon vacancies in panel A (top 15%, corresponding to a greater than 0.4% share of high carbon vacancies); and high share of high-carbon employment in panel B (top 15%, 2000-2017 average, corresponding to a greater than 1.4% share of high carbon employment. Data as used by (*28*) from the BLS's Occupational Employment and Wage Statistics).

Differences in skill requirements

Labour research shows that reallocation costs are proportional to the skill similarity between occupations (*34*). We exploit the rich information on skills contained in EmsiBG data to compare the skill content of low-carbon vis-á-vis fossil fuel and other ads. We focus on five broad skill groups that are in high demand in several sectors and time-consuming to acquire: cognitive, IT, management, social and technical skills. Cognitive, social and managerial skills are more difficult to replace with machines (*2*), while IT skills complement digital technologies in the workplace (*35*). We also consider technical skills that are particularly important for low-carbon jobs and for the adoption of green technologies (*7*). To classify skills into the five skill groups, we use a set of keywords provided by (*20*) for all except IT skills, for which the EmsiBG IT skill family is used (see Table 7), and technical skills for which we use the definition from (*7*).

We compare the relative skill intensity of low-carbon jobs, by plotting the share of low-carbon, high-carbon and generic job ads that contain at least one (extensive margin) or more than one skill (intensive margin) that belong to the 5 groups (Figure 3 and Table 21 in the Appendix). Consistently across all 8 key occupations, low-carbon job vacancies are more likely to require these skills than generic job vacancies, both at the extensive and at the intensive margin. The low-carbon skill gap is particularly pronounced for technical, managerial, and to a lesser extent, social skills. While this confirms a technical-skill bias for green activities previously found in the literature (*7, 15*), job vacancy data reveal additional skill gaps to be filled to prepare workers for the low-carbon transition, especially for skills that are in high-demand by new digital technologies like IT and cognitive. The differences in skill intensity of low-carbon jobs are in most cases statistically significant at conventional levels, when regressing the low-carbon skill gaps across Commuting Zoness (Table 22 of the Appendix).

High-carbon jobs are also more likely to require these five skills than generic jobs, hence the skill gap is relatively narrower between low- and high-carbon than between low-carbon and generic ads. Still, low-carbon vacancies ask for a more complex skill portfolio than high-carbon ones for engineers (see also Table 22). For construction workers, the skill gap is less apparent. For some skills like cognitive and social, the requirement is lower for low-carbon jobs. This suggesting that, if low-carbon jobs are created locally, retraining coal miners to be roofer or weatherization technicians may not be exceedingly costly.

Importantly, our methodology allows to reveal substantial heterogeneity across occupational groups that previous analyses were unable to detect. Some occupations do not follow the general pattern. Notably, we do not detect large skill gaps for business specialists and transportation workers, except for technical skills. Other occupations present larger gaps, such as engineering technicians and installation and maintenance workers, indicating possible difficulties in filling low-carbon vacancies in these occupational groups.

Further exploring heterogeneous reskilling patterns, we examine whether the skill requirements of low-carbon jobs represent a specialization or diversification of skills sets, using two measures of skill coreness. First, a high value of the green skill coreness indicates that skill s is relatively more important in low-carbon ads than in non-low-carbon ads within a given occupation. Second, a high value of the generic skill coreness index implies that skill s is relatively more important in occupation k than in other occupations) (see Appendix **??** for details). Plotting the two indexes in Figure 4), a positive correlation indicates that skills more important in low-carbon vacancies belong to the core skill set of that occupation, thus requiring specialization. A negative correlation, instead, indicates a need for skills diversification. Skills frequently mentioned in both low-carbon and high-carbon engineering ads belong to the core set of skills for this occupation. This implies that incremental retraining may suffice to equip existing workers with core low-carbon skills. Moreover, such retraining may be even easier for fossil fuel engineers moving to low-carbon jobs. Specialization patterns is also pronounced for scientists. In contrast and combined with the previous results on skill gaps, moving into low-carbon for business operation specialists likely involves diversifying the skill set by acquiring new technical, management or social skills that are beyond core curricula in business. The plots exhibit no correlation for construction workers, architects, technicians, installation workers and transport workers. For technicians and installation workers, we document larger skill gaps in Figure 3 but no specialization-diversification patterns. This suggests that, for most of the key occupations in the low-carbon transition, retraining is likely to be highly context- and technology-specific, requiring cooperation among social actors, including trade unions, industrial associations, technical and vocational schools, to find the appropriate solutions.

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 (*20*). The *IT* broad skill corresponds to the eponymous EmsiBG skill cluster family.

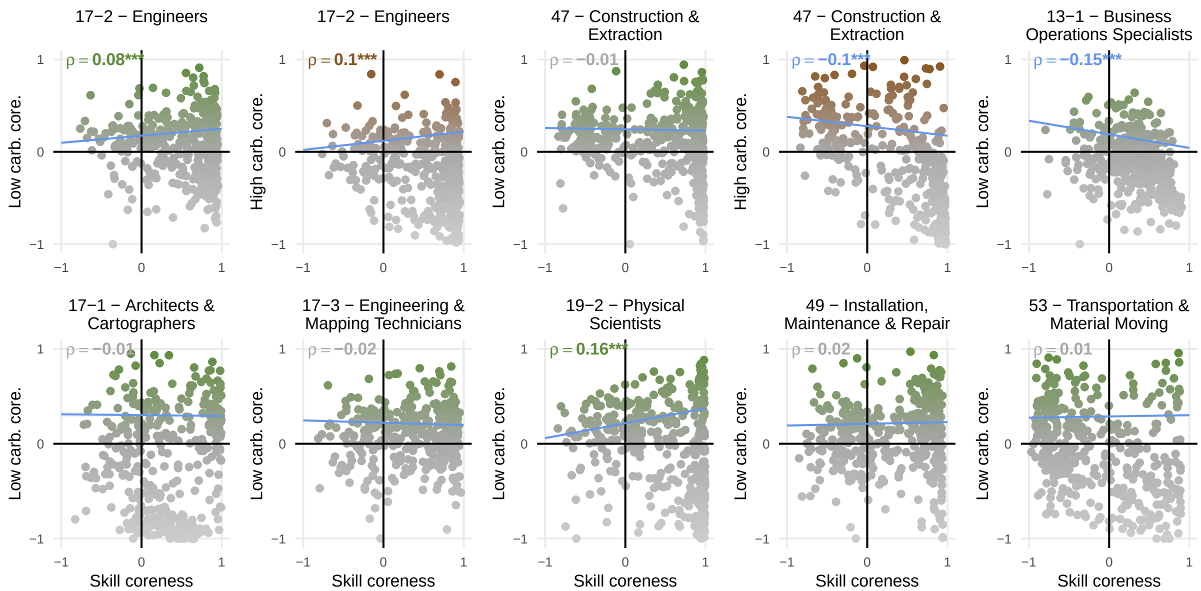

Figure 4: Specialization vs diversification by occupation

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.

The low-carbon wage premium

Wages signal the extent to which low-carbon jobs are attractive for the most talented workers as well as potential skill mismatches and hiring difficulties. Still little is known in the literature regarding the sign and the size of the low-carbon wage premium. (*19*) estimates a 4% wage premium including all green activities and occupations. In contrast, our data allows us to estimate specific wage premia for each occupation and year, focusing on low-carbon activities only. More specifically, we estimate the low-carbon wage premium separately for the major occupational groups through multivariate "mincerian" regressions, using a parsimonious specification including commuting zone fixed effects, binary indicators of the job ad length (a proxy of task complexity), SOC 6-digit and year dummies. These regressions allow us to retrieve the low-carbon wage premium holding constant other characteristics affecting the wage offers. Importantly, what we call low-carbon wage premium only reflects a wage offer (the demand-side) and may differ from the paid wage which is an equilibrium outcome that also accounts for supply-side factors such as the availability of candidates with required competences. The Methods section provides full description and discussion of the regression methodology.

To track the evolution of the "low-carbon wage premium" without reducing sample size, as before we stack the first (2010-2012) and the last three years together (2017-2019). Figure 5 reports the low-carbon wage premium for the eight occupational groups in the two periods. Table 24 in the Appendix shows that results are qualitatively similar in richer specifications with additional covariates.

Three clear patterns emerge. First, there is a positive and statistically significant low-carbon wage premium in the earlier period coinciding with a climate policy boom associated with the American Recovery and Reinvestment Act, for all occupations except architects (17-1). We find very large premium for technicians (13%) and transport workers (16%). The initial low-carbon premium is relatively high (7%) for both installation workers and physical scientists.

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 around 6%, possibly reflecting the difficulties to fill the gap in technical skills in such profession. Finally, the low-carbon wage premium is modest (2%) and only significant at the 10% level for engineers, while the positive wage premium for green construction ads is not statistically significant.

The second pattern is the widespread and pronounced decline of the low-carbon premia in more recent years, which resonates with the political turnaround in the US green policies during the Trump's era, with the withdrawal from the Paris agreement and the repeal of the Clean Power Plan. Importantly, low-carbon wage premium becoming negative and significant at the 10% level for construction workers (-2%), engineers (-4%) and transport workers (-6%). A large decline is also observed for technicians, though a positive and significant low-carbon premium is maintained in the second period (+4%). Low-carbon installation workers experience lesser reductions in the range of wage offers on average, which may reflect the fact that repairing and maintenance tasks are in high demand after construction activities financed by the Obama era green fiscal push. Job vacancies for low-carbon architects buck the trend revealing an increase in the offered pay, but uncertainty is high given the small number of low-carbon ads.

Last, wage offers in high-carbon ads exhibit a less pronounced decline. These jobs historically provide high wages due for example to resource rents and strong unions (*36, 37*), and indeed we document in the Appendix that both construction and engineering jobs offer a high-carbon premium of above 20%, significantly higher than the wage offers for low-carbon ads in similar occupations. The high-carbon premium also declined in the second period but is not small, at around 8% for engineers and 16% for extraction workers. This raises two types of concerns. First, highly talented engineers may be absorbed by high carbon industries, reducing the talent pool available for solving climate change problems through innovation. Second, even if the skill sets of displaced manual workers are suitable for low-carbon activities and local job opportunities are found, lower wage rates that make them worse off will still lead to opposition to climate action.

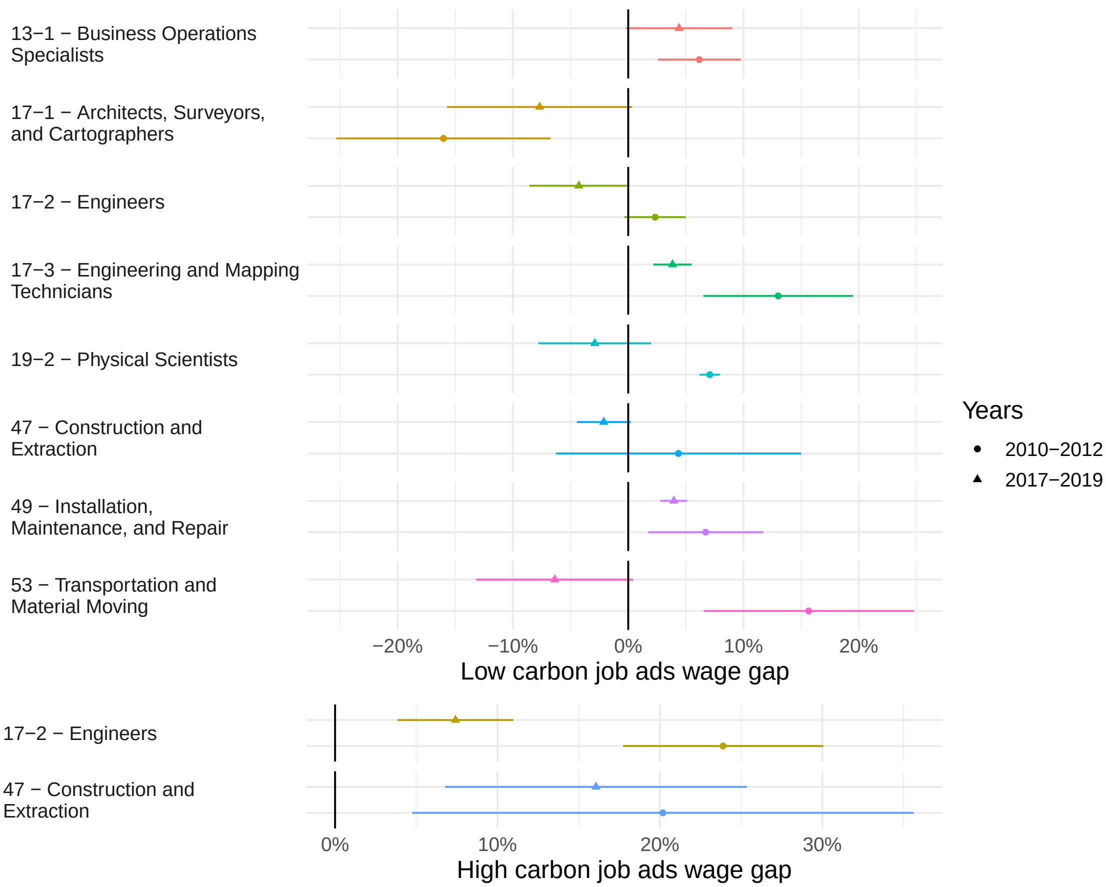

Figure 5: Wage gap between low, high carbon and generic job ads by period

Notes: The logarithm of annual wage reported in a job ad is regressed on an 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. Wages are observed in 22.5% of the ads for the 8 occupations listed, while wages and NAICS codes are observed in 10.2% – 3.2% of which are low-carbon.

Discussion

In contrast to the digital transformation, the implications of the low-carbon transition on workers remain poorly understood. While politicians continue to promise abundant high quality low-carbon jobs to win support for climate policies, there is scant evidence supporting such claims. There is hope that the green, "just" transition will in particular improve labour market conditions for low-skilled workers and offset some of the impacts of the ongoing digital transformation and offshoring, thus help mitigate the rising aggregate inequality and job polarization. Can the low carbon transition indeed deliver a win-win for jobs and the environment?

Perhaps the key obstacle to credibly assessing the labour market impacts of the low-carbon transition has been the lack of a robust, transparent and flexible methodology to define low-carbon jobs. Sector or occupation-based definitions are too coarse to accurately capture low-carbon activity, given that decarbonization affects all corners of the economy, and the greening of jobs is happening within occupations. A broader and more adaptable view of the low-carbon economy is needed to enable analysis of the greenness of jobs, which continues to change as the economy becomes greener.

Another major challenge is the fact that regardless of definition, the number of low-carbon jobs remains extremely low. Consistent with previous literature (*19*), we estimate that the share of low-carbon vacancies in the US economy has been constant around 1.3%. The backdrop of our study is that of very modest climate action. US emissions fell 8% from 5,594 to 5,144 $MtCO_2$ during our study period 2010-2019 (*38*), while the Biden administration has committed to cut emissions by at least 50% by 2030 compared to 2005 levels (*39*). The precise assessment of skill requirements of low-carbon activities will become even more important as a large scale mobilization of capital and labour towards carbon neutrality is expected, to meet targets pledged under the Paris Agreement. Labour reallocation towards low-carbon activities will be massive under ambitious decarbonization scenarios (*12, 14*).

This paper demonstrates that job ad data can be a powerful tool to examine labour market consequences of the low-carbon transition. Our method, combining natural language processing and expert elicitation, enables accurately isolating low-carbon job ads and exploring emerging skill and wage gaps at a very granular level of occupational aggregation. Our approach allows for quantifying reskilling requirements across regions and occupations, and can thus help improve reallocation cost estimates; for example, by informing integrated assessment and computational general equilibrium models, used to assess macroeconomic impacts of climate change mitigation. At the micro-level, using our approach can aid policymakers in monitoring skill gaps associated with specific technologies and sectors that are relevant for the local economy, thus improving the effectiveness and the targeting of retraining programs.

We observe some stylized facts from the data on existing low-carbon jobs that can inform policies in more ambitious decarbonization scenarios. We document a rise in the share of low-carbon jobs among low-skilled occupations during the period 2010-2019, and a fall in the share among high-skilled occupations. This finding tentatively suggests that the low-carbon transition could contribute to offset secular deterioration of the labour market conditions for unskilled workers.

We also find limited geographic overlap between low- and high carbon jobs. This suggests the labour market effects of the low-carbon transition could compound existing regional disparities if low-skilled displaced workers face limited alternative employment opportunities locally. To prevent manual fossil workers being left behind, there may be a potential role for targeted place-based policies for these communities and their labour markets to adjust towards a carbon neutral world. Interpretation of our descriptive results, however, should be cautious given how little is know around the speed, extent and nature of green jobs creation in local labour markets.

Our most clear finding is that low-carbon vacancies systematically differ in their skill requirements. Low-carbon vacancies exhibit higher frequency of skills in all occupations, suggesting they are more skills intensive than generic job ads than previously thought (*7*). This finding is important because reallocation costs are likely proportional to the reskilling requirement of the workforce (*7, 34*). It implies that the reallocation costs may be greater than previous research has found. We document a broad skills gap across all skill groups. The gap is biggest for technical and managerial skills, but also found in skill groups important for the digital transformation of our economies such as cognitive and IT. However, skill gaps and reskilling paths appear highly heterogeneous. In some occupations, such as managers, low-carbon tasks require a diversification of skill sets. In other occupations, such as engineers and scientists, low-carbon jobs require further specialization in the skills that are already core to that occupation. It also suggests that finding retraining solutions will be complex, and may need to be tailored to meet the specific needs of the companies hiring these workers, particularly for occupational groups such as engineering technicians and installation workers where no clear pattern is found.

We find evidence that high- and low-carbon jobs demand a similar set and level of skills but high-carbon jobs offer markedly higher wages. The latter may in part be driven by resource rents as well as collective bargaining among fossil fuel workers (*36*), in contrast to low-carbon workers that are spread across the economy, as we document (see Table 12). Reconciling the gap between higher skill requirements and the lack of wage premia to compensate for human capital investments that are specific to operate low-carbon technologies represents a neglected but important issue for managing the low-carbon transition. Moreover, high-carbon jobs are well-paid in relatively poorer regions, which contributes to explaining the political opposition against ambitious climate policies of such regions (*29, 32*). Because demand for low-carbon activities is primarily driven by policy, the widespread decline in green wage premia in the last decade may reflect the sudden boom and bust in US climate policy. Further research is needed to uncover factors driving the inadequate wage premium found for low-carbon vacancies, to ensure a workforce fit for the low-carbon transition.

Methods

Identifying low-carbon ads

Accurately identifying low-carbon jobs ads is an important step to compare low-carbon and non low-carbon job ads within the same occupation. In this section we describe the three step procedure developed to identify low-carbon job ads from the near-universe sample of US online job ad data collected by Emsi Burning Glass.

Step 1: selecting low-carbon keywords

To select keywords associated with low-carbon economic activities, we utilise two pre-existing and widely utilised classifications. First, the Occupational Information Network (O*NET) dataset provides information on specific task contents of narrowly defined occupations (867 BLS Standard Occupational Classification (SOC) occupations), indicating tasks that are considered 'green'. Examples of the textual descriptions of tasks 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."

The definition of 'green' tasks, which was added to the dataset under the Green Economy Program of 2009, covers not only climate change related tasks, but also tasks that contribute towards non-climate environmental problems such as waste management, remediation activities, and activities associated with local air and water pollution[1]. We utilise a complementary sector classification (SOC 6-digit level) to isolate the tasks relevant to CO_2 mitigation or adaptation, from general green activities. Specifically, we select only a subset of green specific

[1]See `https://www.onetcenter.org/reports/GreenTask.html` for more details.

tasks performed in the following green sectors: "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 of low-carbon green tasks in O*NET include:

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

while non low-carbon green tasks include:

- "Monitor and adjust irrigation systems to distribute water according to crop needs and to avoid wasting water."
- "Prepare hazardous waste manifests or land disposal restriction notifications."
- "Advise land users, such as farmers or ranchers, on plans, problems, or alternative conservation solutions."

'To extract keywords from these O*NET task descriptors, we first tokenize them, keeping only nouns, adjectives, verbs and adverbs. We then apply natural language processing (NLP) using the term frequency–inverse document frequency (TF-IDF) algorithm (*40*) on the low-carbon and non low-carbon subsets of tasks in O*NET. This yields a relevance score for every keyword in each of the two subsets. For each keyword in the low-carbon subset, we then take the difference in the relevance score obtained within the low-carbon subset of tasks (s_g) and the one obtained in the non low-carbon subset (s_{ng}), normalizing to a zero score for words that only appear in one of the two lists. This step provides us with a low-carbon likelihood (LCL) for each keyword appearing in the O*NET task descriptions. In particular, $LCL = s_g - s_{ng}$. The LCL measures the extent to which each keyword is specific to low-carbon tasks rather than being a general characteristic describing the occupational task content. Obviously, negative value of the LCL index are assigned to keywords not characterising low-carbon activities, while positive LCL are indicates relevance for such activities.

We apply a similar approach to the PRODCOM classification by contrasting the textual descriptions of climate change mitigation relevant products identified by (*41*) with that of other products.

Examples of low-carbon products in PRODCOM include:

- "Frames and forks, for bicycles"
- "Multiple-walled insulating units of glass"
- "Vehicles with an electric motor"

We then combine the two lists and sort them by the LCL index defined above. We keep the top 250 of these to get a set of *low-carbon* (climate-related) keywords. The LCL index is distributed as a steeply decreasing power law, becoming essentially flat beyond rank 30. Thus the exact choice of cutoff does not substantially affect the results of our classification exercise. Limiting the total number of keywords used to 250 is further motivated by computational considerations, as matching against a list of keywords increases quadratically with the number of words in the list.

Step 2: Mapping low-carbon keywords with EmsiBG job identifiers.

We proceed to match our list of 250 low-carbon keywords against the 16,000 EmsiBG skills, to identify a subset of low-carbon skills /job identifiers. To do so, we use the natural language processing algorithm Word2Vec (*26*) to semantically match each job identifier word against our 250 low-carbon keywords, yielding a matching score for each job identifier.

Semantic matching with word embeddings (such as Word2Vec) is more robust than more naïve, string-based / fuzzy matching approaches (e.g. using 'wind*' to match both 'wind power' and 'wind mill'). For example, 'solar' and 'photovoltaics' are recognized as being semantically similar, even though they would be considered unrelated with naïve fuzzy matching. Word embeddings rely on a language model trained on a corpus of text to identify semantic similarities between words, based on their patterns of co-occurrence with other words (e.g. the model will pick up from observing "The king rules the country", "The queen rules the land", and "The prince governs the county" that 'king', 'queen' and 'prince' are close semantically). Each word is thus represented as a vector in this feature space. The generalized cosine distance in that vector space measures semantic proximity. Here we use the pre-trained word embedding model provided by Google for the English language, Word2Vec, trained on the Google News dataset, which comprises around 100 billion words. At a mathematical level, each word is projected onto a number of dimensions (called the feature space, numbering a few hundreds in the case of Word2Vec). The power of this approach resides in the fact that, like many deep learning techniques, it is unsupervised: the feature space doesn't need to be designed by the implementer, and is instead built endogenously by the model.

To increase the robustness of the procedure against the choice of cutoff in the first step, we re-weight the matching score using the individual keywords' LCL. We automatically retain those EmsiBG job identifiers that achieve a direct string match against one of the top 20 low-carbon keywords collected in the first step. For instance, the keyword 'solar' matches the EmsiBG identifier 'Solar Engineering' directly. These form our initial 396 low-carbon job identifiers and conclude the unsupervised portion of our classification algorithm. A zero matching score identifies non-low-carbon job identifiers, which represent the overwhelming majority of the cases. Yet, we find that approximately 600 BG identifiers 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.

Step 3: Expert elicitation survey

To resolve ambiguous cases, we asked experts in the field of climate change to classify job identifiers as low-carbon or not through an online survey. Responses were obtained from 50 climate experts at leading institutions including Oxford University, the London School of Economics, the OECD and the University of Venice (invitation email presented below).

Each expert was tasked to designate 120 job identifiers as low-carbon or non-low-carbon. Of these job identifiers, 100 were randomly sampled from the set of 600 ambiguous identifiers described above, while 20 were sampled from the 396 low-carbon identifiers found through a perfect match with our low-carbon keywords. The latter subset was included to verify the quality of the expert's classification skills as well as to corroborate the previous step of the procedure.

We exclude responses from experts that did not correctly classify at least 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 threshold score of 0.9 to obtain a further 49 low-carbon job identifiers.

Definition of low-carbon ads

The three-step process described yields 445 low-carbon identifiers in total. We define low-carbon job ads as those that contain *at least* one of the 445 low-carbon job identifiers. Table 1 presents examples of low-carbon job ads and informations contained in it including location, degree and annual wage. The last column contains examples of EmsiBG skills, highlighting the low-carbon identifier in bold. Non low-carbon skills are important for the analysis of section where we compare the skill sets of low-carbon to other ads within the same occupation.

To give some intuitive insights on the methodology, Table 2 lists the top 50 low-carbon identifiers. Besides bus driving, insulation, energy efficiency (or conservation) and renewable energy stand out as the most frequent identifiers. Note the inclusion of several identifiers related to building retrofitting and weatherization that were heavily subsidized under the green ARRA program (*28*).

Table 1: 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 Cuca-monga, 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

Table 2: 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

Expert survey email

Dear [Expert name],

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 ad 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,

Table 3: low-carbon job identifiers/ low-carbon skills

Air Emissions	Biomass Research	Building Energy Modeling (BEM)
Air Permitting	Biomass Thermochemical Conversion	Direct Methanol Fuel Cells
Air Pollution Control	Biomass Transformation	Directed Energy Systems
Air Quality Control	Biorefinery	Dressing Changing
Air Quality Regulations	Building Energy Codes	EPA Regulation
Air Quality Remediation	Building Energy Modeling Software	Efficient Transportation
Air Quality Standards	Building Envelope Evaluation	Electric Car Industry Knowledge
Alternative Air Conditioning	Bus Driving	Electric Vehicle
Alternative Energy	Bus Industry Knowledge	Emission Reduction Projects
Alternative Energy Design	Bus Kneeling Systems	Emissions Analysis
Alternative Energy Evaluation	Bus Safety	Emissions Analyzer Operation
Alternative Fuel Vehicles	Carbon Accounting	Emissions Analyzers
Alternative Fuels	Carbon Asset Management	Emissions Control Systems
Alternative Transportation	Carbon Dioxide Flooding	Emissions Inspection
Automatic Insulation Strippers	Carbon Emissions Reduction	Emissions Inventories
Automotive Energy Management	Carbon Footprint	Emissions Management
Bicycle Planning	Carbon Footprint Reduction	Emissions Mitigation
Bike Industry Knowledge	Carbon Management	Emissions Monitoring
Bike Repair	Carbon Offsets	Emissions Reduction
Biodiesel	Carbon Reduction	Emissions Reduction Strategy
Biodiesel Development	Clean Air Act	Emissions Standards
Biodiesel Industry Knowledge	Clean Energy	Emissions Testing
Biodiesel Production	Clean Technology	Energy - Efficient Systems
Biodiesel Research	Clean Technology Investment Opportunities	Energy Conservation
Biodiesel Technology	Cleantech Products	Energy Conservation Measures
Biofuel Product Development	Climate Analysis	Energy Cost Reduction
Biofuel Production	Climate Change	Energy Efficiency
Biofuels Applications	Climate Change Analysis	Energy Efficiency Analysis
Biofuels Development	Climate Change Impact	Energy Efficiency Assessment
Biofuels Extraction	Climate Change Mitigation Intiatives	Energy Efficiency Consultation
Biofuels Plant Safety	Climate Change Policies	Energy Efficiency Improvement
Biofuels Processing	Climate Change Principles	Energy Efficiency Products
Biofuels Processing Equipment	Climate Change Processes	Energy Efficiency Research
Biofuels Production Adjustment	Climate Change Programs	Energy Efficiency Services
Biofuels Production Management	Climate Change Research	Energy Efficiency Supervision
Biofuels Quality Assessment	Climate Change Simulations	Energy Efficiency Technologies
Biofuels Research	Climate Data Analysis	Energy Efficient Building
Biofuels Research and Development	Climate Information	Energy Efficient Home Improvement
Biofuels Technology	Climate Management Research	Energy Efficient Lighting
Biomass	Climate Outreach	Energy Efficient Operations
Biomass Conversion	Climate Policy	Energy Efficient Transportation
Biomass Determination	Climate Prediction	Energy Loss Reduction
Biomass Equipment	Climate Research	Energy Measurement Devices
Biomass Feedstock Measurement	Climate Systems	Energy Policy
Biomass Fuel Gasification Systems	Climate Theory	Energy Reduction
Biomass Gasification Processes	Commercial Solar Projects	Energy Saving Plumbing Systems
Biomass Plant Equipment	Commercial Solar Sales	Energy Saving Products
Biomass Power Production	Concentrated Photovoltaic Technology	Energy Savings Calculations
Biomass Processing Equipment	Cooling Efficiency	Energy Star Documentation
Biomass Production	Dam Construction	Energy Supply Side Savings

Table 4: low-carbon job identifiers/ low-carbon skills (cont.)

Energy Usage Tracking	Green Energy Promotion	Light Rail
Energy-Efficient Appliances	Green Job Development	Light Rail Transit Systems
Environmental Sustainability	Green Manufacturing	Locomotive Engineering
Ethanol	Green Marketing	Locomotive Inspection
FRET (Fluorescence Resonance Energy Transfer)	Green Plumbing	Locomotive Safety
Federal Railroad Administration	Green Plumbing Equipment Installation	Loose Insulation
Federal Transit Administration	Green Procurement	Low Carbon Projects
Fuel Cell	Green Real Estate	Low Carbon Solutions
Fuel Cell Analysis	Green Retail	Low Energy Buildings
Fuel Cell Applications	Green Retrofitting	Mass Transit Industry Knowledge
Fuel Cell Assembly	Green Roof Design	Methane Gas Collection System
Fuel Cell Design	Green Roof Installation	Methane Monitors
Fuel Cell Development	Green Roofing	Mitigation Projects
Fuel Cell Engineering	Green Stocks	Monorail
Fuel Cell Generator	Green Strategy	Non-Point Source Pollution
Fuel Cell Modeling	Green Supplier	Organic Photovoltaics (OPV)
Fuel Cell Performance Improvement	Green Techniques	PV System Design and Drafting
Fuel Cell Research	Green Technology	Photovoltaic (PV) Energy Production
Fuel Cell System Design	Green Transportation	Photovoltaic (PV) Equipment
Fuel Cell Testing	Green Walls	Photovoltaic (PV) Systems
Fuel Cell Testing Equipment	Greenhouse Gas	Photovoltaic Energy
Fuel Cell Theory	Greenhouse Gas (GHG) Emissions	Photovoltaic Solutions
Fuel Cell Validation	Greenhouse Gas Accounting	Photovoltaic System Design
Fuel Cell Vehicles	Hazardous Energy Control	Photovoltiac (PV) Module Evaluation
Fuel Efficiency	Heat Pump Installation	Pipe Insulation
Geothermal	Heat Pump Maintenance	Plumbing Pipe Insulation
Geothermal Energy Plants	Heat Pump Repair	Pollution Control
Geothermal Heat Systems	Heavy Rail	Pollution Control Equipment
Geothermal Loop Systems	Heavy Rail Transit Systems	Pollution Control Systems
Geothermal Plant Equipment	High Speed Rail	Pollution Prevention
Geothermal Plant Operations	Home Energy Assessment	Pollution Regulation
Geothermal Production	Home Energy Rating	Pollution Source Identification
Geothermal Production Management	Hybrid Buses	Pollution Underwriting
Geothermal Sales	Hybrid Vehicle	Polymer Electrolyte Membrane Fuel Cells
Global Warming	Hydroelectric Power	Public Transit Operations
Global Warming Pollution	Hydrogen Production	Public Transit Systems
Green Architecture	Hydropower	Public Transportation
Green Automotive Technologies	Hydropower Plant Equipment	Public Transportation System
Green Building	Hydropower Technology	Rail Bridge Design
Green Building Standards	Installing LED Lighting	Rail Equipment Maintenance
Green Certified Construction Practices	Insulation	Rail Equipment Repair
Green Chemistry	Insulation Efficiency	Rail Industry Knowledge
Green Chemistry Methods	Insulation Installation	Rail Operations
Green Communities	Landfill Design	Rail Safety
Green Contractor	Landfill Gas Collection	Rail-Track Laying
Green Design	Landfill Gas Collection System Operation	Railroad Conducting
Green Distributor	Landfill Inspection	Railroad Design
Green Education	Landfill Operations	Railroad Engineering
Green Energy	LEED	Railroad Law
Green Energy Marketing	LEED Rating System	Railroad Operating Rules

Table 5: low-carbon job identifiers/ low-carbon skills (cont.)

Railroad Safety	Solar Farm	Sustainable Living
Railway Signaling	Solar Heat Absorption Reduction	Sustainable Manufacturing
Railway Systems	Solar Heating	Sustainable Materials
Renewable Energy	Solar Hot Water Heating Systems	Sustainable Packaging
Renewable Energy Consultation	Solar Installation	Sustainable Systems
Renewable Energy Development	Solar Manufacturing	Tidal Power
Renewable Energy Equipment	Solar Module Assembly	Trams
Renewable Energy Industry Knowledge	Solar Panel Assembly	Waste - to - Energy Conversion Systems
Renewable Energy Installation	Solar Panel Attachment	Waste-to-energy
Renewable Energy Markets	Solar Panel Fitting	Water Pollution Control
Renewable Energy Supply	Solar Panels	Water Pollution Source Identification
Renewable Energy Systems	Solar PV Generation Systems	Weatherization
Renewable Resources	Solar PV Hot Water Heating Systems	Weatherization Installation
Renewable Sales	Solar Photovoltaic Business Development	Wind Commissioning
Residential Energy Auditing	Solar Photovoltaic Design	Wind Consultation
Residential Energy Conservation	Solar Photovoltaic Engineering	Wind Energy Engineering
Residential Energy Efficiency	Solar Photovoltaic Installation	Wind Energy Industry Knowledge
Residential Energy Sales	Solar Photovoltaic Panels	Wind Energy Operations
Retrofitting	Solar Photovoltaic Performance Improvement	Wind Energy Operations Management
Roof Insulation Surfaces	Solar Photovoltaic Research	Wind Energy Project Management
Rubber Dam Placement	Solar Photovoltaic Technology	Wind Energy Project Planning
Rubber Dam Removal	Solar Power Electrical Work	Wind Farm Analysis
Self-Adjusting Insulation Stripper	Solar Power Purchase Agreement Sales	Wind Farm Construction
Silicon Solar Cell	Solar Power System Design	Wind Farm Design
Smart Grid	Solar Products	Wind Field Operations
Smoke Emissions Reduction	Solar Purchasing Management	Wind Generator Assembly
Solar Application	Solar Roofing System Installation	Wind Integration Studies
Solar Array Production Calculation	Solar Roofs	Wind Measurement
Solar Boilers	Solar Sales	Wind Power
Solar Cell	Solar Sales Management	Wind Power Development
Solar Cell Design	Solar Start Ups	Wind Project Construction
Solar Cell Equipment	Solar Systems	Wind Project Development
Solar Cell Manufacturing	Solar Technology	Wind Project Engineering
Solar Cell Manufacturing Equipment	Solar Thermal Installation	Wind River
Solar Collector Installation	Solar Thermal Systems	Wind Turbine Construction
Solar Consultation	Solar and Wind Energy	Wind Turbine Control System
Solar Contractor	Spray Foam (Insulation)	Wind Turbine Equipment
Solar Design	Sungard Energy	Wind Turbine Equipment Testing
Solar Development	Sustainability Campaigns	Wind Turbine Fabrication
Solar Electric Installation	Sustainability Consulting	Wind Turbine Performance Improvement
Solar Energy	Sustainability Evaluation	Wind Turbine Production
Solar Energy Components	Sustainability Improvement	Wind Turbine Service
Solar Energy Industry Knowledge	Sustainability Marketing	Wind Turbine Technology
Solar Energy Installation Management	Sustainability Procedures	Wind Turbines
Solar Energy System Development	Sustainability Research	Zero- Energy Buildings
Solar Energy System Installation	Sustainable Agriculture	
Solar Energy Systems	Sustainable Architecture	
Solar Energy Systems Engineering	Sustainable Design	
Solar Engineering	Sustainable Energy	
Solar Equipment	Sustainable Engineering	

The Emsi Burning Glass dataset

Description

Emsi Burning Glass (EmsiBG) uses web scraping to collect data on job posting from approximately 50,000 online job boards as well as company websites (*42*), removes duplicates and parses into a systematic, usable format. For each job ad, EmsiBG extracts job characteristics information including occupation, educational qualifications requirements, skills, employer characteristics, location and wage. EmsiBG data thus allows us to observe changes in skill requirement at the job level, and compare similar jobs within the same occupation, improving the granularity of analysis relative to previous work looking at changes in the task content at the occupation level.

EmsiBG extracts around 16,000 unique skills (job identifiers) from job ads, which is a canonicalised version of skills contained in the job ads. A large portion of these skills (6,959 or 44%) are also assigned a skill cluster (groupings of skills that have similar functionality) and a skill cluster family (the most general layer of the EmsiBG skill taxonomy). For example, the skill "smart grid" belongs to the skill cluster "electrical construction" in the skill family "architecture and construction".

Figure 6 shows the average number of skills listed per job ad over time and job category (generic, high carbon and low-carbon). The number of skills per position advertised has trended upwards over the period of observation across all job categories, with the median skill count growing from 6 to 8 from 2010 to 2019. The number of skills contained in low-carbon vacancies has been consistently higher over the entire decade, reaching a median value of 12 skills per low-carbon ads in 2019, compared with 8 for generic ads and 9 for high carbon ads.

Variation in skill vector length in general, and the longer skill vector length for low-carbon job ads specifically may be attributed to a number of factors. First, more complex jobs contain more skills in ads. It could also be attributed to marketing strategies of firms trying to attract talent to low-carbon jobs by providing excessively detailed job descriptions to partly offset low wage offers – which we do not observe. More skills may be found in postings for new job types – new, unfamiliar low-carbon positions may be described in more detail to ensure a good candidate match, compared to the average job.

Figure 7 highlights the heterogeneity in skill vector lengths across major occupational groups. As expected, 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.

Representativeness

Burning Glass data aims to be a near-universe of online job postings and is increasingly used in research. However, it is also well known that it over-represents growing firms (*43*) and certain occupations such as business & financial, computer & mathematical, and healthcare occupations and under-represents construction, public administration& government, mining & logging, and accommodation & food services (*42*). Further, online job vacancies data capture changes in labour demand, rather than the stock of employment population. 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.

Growing firms or occupations are over-represented and many jobs are not posted online, including self-employment. In our analyses, we partially restore representativeness by re-weighting low-carbon jobs using BLS employment shares (Table 6). Our estimate on low-carbon jobs are in the ballpark of previous estimates of the share of green jobs (*19, 28, 44, 45*) though on the lower end, which can be attributed to the focus on low-carbon activities excluding green activities such as water and waste.

Table 6: Representativeness of Burning Glass Technologies 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%

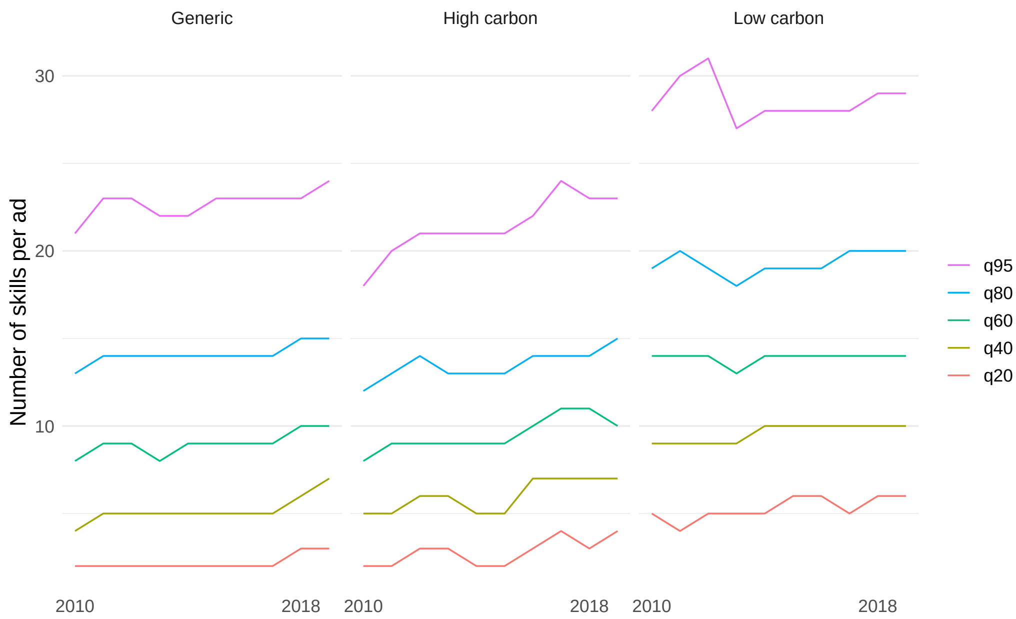

Figure 6: Distribution of the number of skills per job ad by category over time

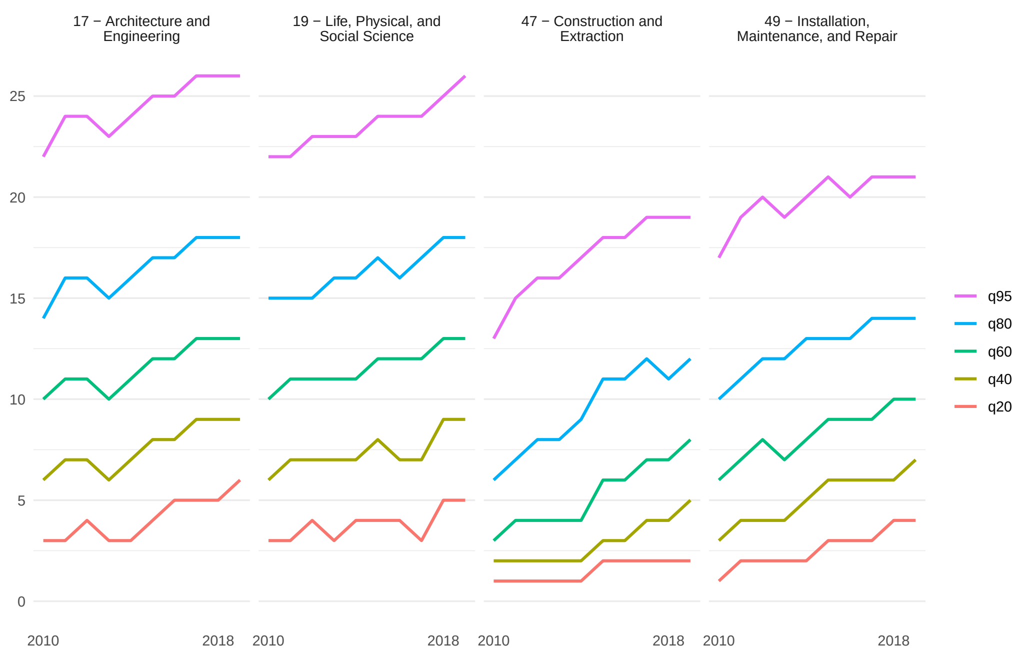

Figure 7: Distribution of the number of skills per job ad – Heterogeneity across occupations

Low and high carbon skill coreness index

To analyse whether the skill requirements of low-carbon jobs represent a specialisation or diversification of skills sets, we analyse the correlation between two indices : a generic skill coreness index G_s^{SOC} and a low (resp. high) carbon skill coreness index C_s^{SOC}. These indices are defined within each SOC occupational groups (at the 2- or 3-digit level) as follows:

$$G_s^{SOC} = \frac{g_s^{SOC} - 1}{g_s^{SOC} + 1} \qquad g_s^{SOC} = \frac{n_s^{SOC}}{n^{SOC}} / \frac{n_s}{n}$$

$$C_s^{SOC} = \frac{c_s^{SOC} - 1}{c_s^{SOC} + 1} \qquad c_s^{SOC} = \frac{n_s^{c,SOC}}{n^{c,SOC}} / \frac{n_s^{SOC}}{n^{SOC}}$$

where n_s^{SOC} is the number of ads requiring skill s in occupational group SOC
n^{SOC} is the number of ads in occupational group SOC
n_s is the number of ads requiring skill s in the entire sample
n is the total number of ads in the sample
$n_s^{c,SOC}$ is the number of low (resp. high) carbon ads requiring skill s in occupational group SOC
$n^{c,SOC}$ is the number of low (resp. high) carbon ads in occupational group SOC
n_s^{SOC} is the number of ads requiring skill s in occupational group SOC
n^{SOC} is the number of ads in occupational group SOC

The generic skill coreness index g_s^{SOC} compares skill s's importance or coreness in SOC j to its coreness across all occupations. A value of g_s^{SOC}above 1 indicates that skill s's coreness in SOC j is greater than its coreness across all occupations, indicating it is more in demand by SOC. The low- (or high-) carbon skill coreness index c_s^{SOC} compares skill s's coreness in low- (or high-)carbon jobs in SOC j to its coreness in SOC j overall including generic jobs. A value of c_s^{SOC}above 1 indicates that skill s's coreness in low-(or high-) carbon jobs in SOC j is greater than its coreness across all jobs in SOC j, indicating it is more in demand by low- (or high-)

carbon jobs within SOC j.

The distribution of G_s^{SOC} and C_s^{SOC} symmetrically ranges from -1 to +1 with 0 being the neutral point.

If and only if:

$$corr(G_s^{SOC}, C_s^{SOC}) > 0$$

then the skills required for low-carbon jobs in occupation j belong to the core set of skill sets demanded by that occupation, thus indicating that a transition to low-carbon jobs will require workers to expand their skill profile by further specialisation in their area of work.

Conversely, if and only if:

$$corr(G_s^{SOC}, C_s^{SOC}) < 0$$

then the increase in skill requirements of low-carbon jobs in occupation j instead demands workers to diversify their skill-sets and acquire new skills that don't belong to the usual skill profile of their occupation.

Table 7: 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*

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 the eight main occupational groups considered in our analysis:

$$\log\left(w_{it}\right) = \beta_{lc}\mathbb{1}\{i \in lc\} + \sum_{k} \mu_k + \alpha_t + \varepsilon_i$$

where $w_i t$ is the annual wage as posted in the ad. Wage is logged to mitigate the influence of outliers. 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. Controls μ_k include occupation (6-digit SOC), industry (2-digit NAICS) and commuting zones, respectively. These controls purge the low-carbon wage premium from the influence of obvious confounders, such as unobserved industry-level and regional shocks. Moreover, we control flexibly for the length of the skill vector in the job ad using a set of five dummy variables for a corresponding number of skill vector length bins (1-4, 5-8, 9-12, 13-16, 17+). Together with a set of dummies indicating the education level required in the ad, these controls capture both the complexity of the job post and the differences in advertising styles across companies.

Wage information are available for approximately 20% of job ads, thus, to mitigate concerns related to the representativeness of our estimation sample, we weight regressions by the BLS employment of the 6-digit occupation. Unfortunately, the number of job ads with missing information on education and sector is very large reducing the size of the estimation sample by 65% and 55%, respectively. We thus use a parsimonious specification with only years, occupation, CZ and job length dummies in the main specification, while testing the robustness of our results to the inclusion of additional controls. Finally, to limit the influence of outliers, we exclude ads comprising more than 100 skills.

Slightly abusing of terminology, what we call low-carbon wage premium only reflects a wage offer (the demand-side) and may differ from the actually paid wage which is an equilibrium outcome that also accounts for supply-side factors such as the availability of candidates with required competences. (*20*) and (*46*) 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 (*19*). To complement such approach, we thus decide to estimate occupational-specific differences in wage offers between low-carbon and generic job ads.

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 here. In turn, we are well aware that unobserved firm characteristics are highly correlated with the wage offered, but including firm fixed effects is unfeasible since 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 a 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 (*47*), it is not enough to argue that our estimates of the low-carbon wage premium are downwardly biased.

Data availability statement. The job ads data used in this research was provided by Emsi Burning Glass. The contractual agreement restricts public posting of the data set. The dataset can however be purchased from Emsi Burning Glass.

Code availability statement. Code for data cleaning and analysis is provided as part of the replication package. It will be uploaded on the Corresponding Author's Github public profile

once the paper has been conditionally accepted. [INSERT LINK HERE CONDITIONAL ON PAPER BEING ACCEPTED.]

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Supplementary Information

Descriptive statistics

In this article, we use the common definition for high and low skilled occupations within the SOC classification: occupational major groups 11 to 29 are labeled high skilled, while major groups 31 to 53 are labeled low skilled.

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

Table 8: 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%

Table 9 highlights the heterogeneity in the intensity of low-carbon ads within 2-digit SOC occupations. For instance, among the Business and Finance occupations (SOC 13), only Business Specialists (SOC 13-2) have a high share of low-carbon ads. 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%.

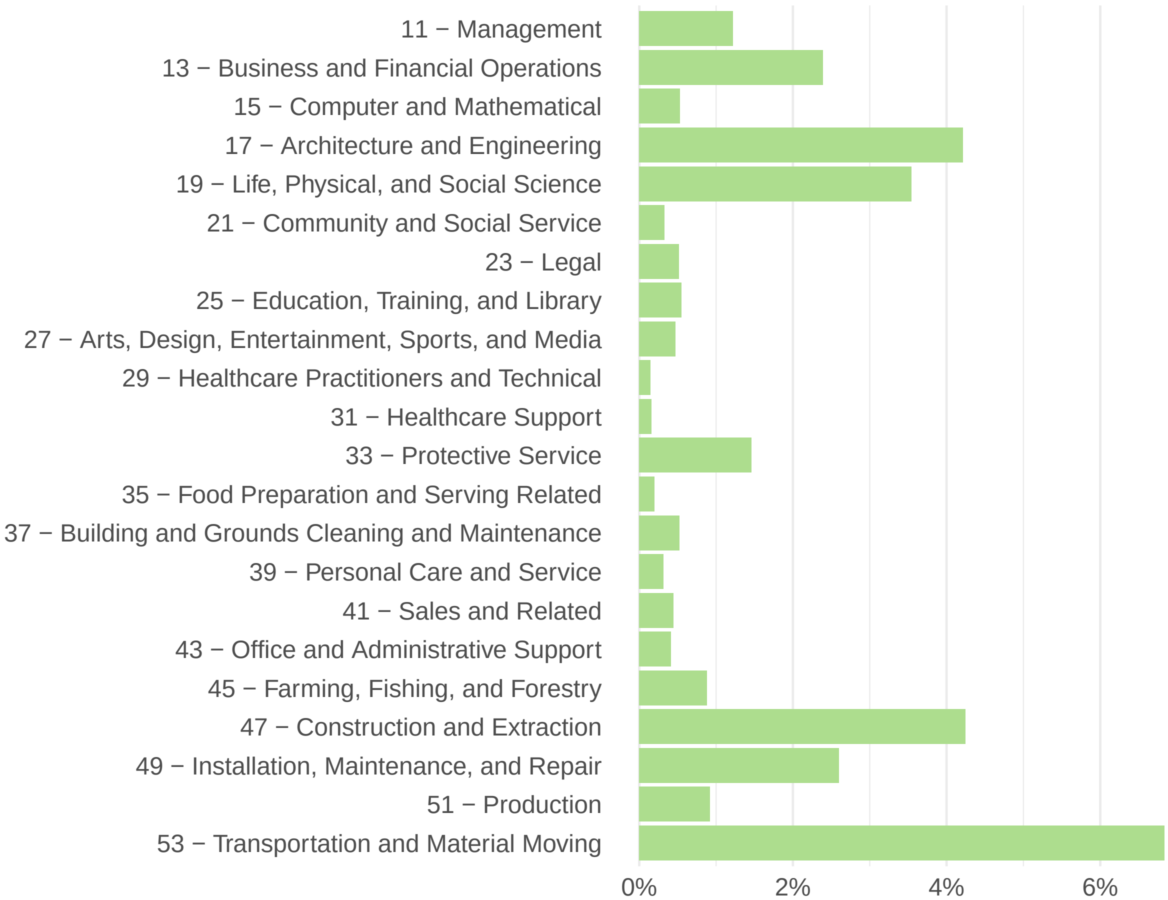

Figure 8: Low-carbon ads intensity by occupation (2010-2019)

Table 9: 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 10: 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	99,572	4.1%
47-1 - Supervisors of Construction and Extraction Workers	3,658	3.2%
47-2 - Construction Trades Workers	12,356	0.8%
47-3 - Helpers, Construction Trades	82	0.2%
47-4 - Other Construction and Related Workers	3,612	2.1%
47-5 - Extraction Workers	90,530	100.0%
Total	209,810	0.3%

Table 11: 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%

Notes: Table 11 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.

Table 12: Share of low-carbon ads by NAICS sector (unweighted averages, 2010-2019)

	Ad count			Unweighted ad share		
NAICS2	Generic	Low carbon	High carbon	Generic	Low carbon	High carbon
11 - ”Agriculture, Forestry, Fishing and Hunting”	99,584	1,968	149	97.9%	1.9%	0.1%
21 - ”Mining, Quarrying, and Oil and Gas Extraction”	474,446	8,440	70,808	85.7%	1.5%	12.8%
22 - Utilities	483,609	69,603	6,593	86.4%	12.4%	1.2%
23 - Construction	1,598,110	64,288	3,931	95.9%	3.9%	0.2%
311 - Food Manufacturing	577,092	5,114	131	99.1%	0.9%	0.0%
312 - Beverage and Tobacco Product Manufacturing	347,768	2,072	1,291	99.0%	0.6%	0.4%
313 - Textile Mills	691	8	0	98.9%	1.1%	0.0%
314 - Textile Product Mills	41,297	397	14	99.0%	1.0%	0.0%
315 - Apparel Manufacturing	79,365	103	2	99.9%	0.1%	0.0%
316 - Leather and Allied Product Manufacturing	5,585	6	1	99.9%	0.1%	0.0%
321 - Wood Product Manufacturing	90,915	3,409	322	96.1%	3.6%	0.3%
322 - Paper Manufacturing	83,421	651	78	99.1%	0.8%	0.1%
323 - Printing and Related Support Activities	83,422	245	67	99.6%	0.3%	0.1%
324 - Petroleum and Coal Products Manufacturing	112,773	5,033	21,616	80.9%	3.6%	15.5%
325 - Chemical Manufacturing	1,540,097	12,637	1,094	99.1%	0.8%	0.1%
326 - Plastics and Rubber Products Manufacturing	74,002	698	6	99.1%	0.9%	0.0%
327 - Nonmetallic Mineral Product Manufacturing	173,885	3,121	994	97.7%	1.8%	0.6%
331 - Primary Metal Manufacturing	121,384	1,632	784	98.0%	1.3%	0.6%
332 - Fabricated Metal Product Manufacturing	215,079	1,641	150	99.2%	0.8%	0.1%
333 - Machinery Manufacturing	761,968	13,694	489	98.2%	1.8%	0.1%
334 - Computer and Electronic Product Manufacturing	1,568,119	19,823	756	98.7%	1.2%	0.0%
335 - ”Electrical Equipment, Appliance, and Component Manufacturing”	127,518	4,277	69	96.7%	3.2%	0.1%
336 - Transportation Equipment Manufacturing	1,339,451	23,786	802	98.2%	1.7%	0.1%
337 - Furniture and Related Product Manufacturing	76,814	2,787	84	96.4%	3.5%	0.1%
339 - Miscellaneous Manufacturing	388,605	1,416	48	99.6%	0.4%	0.0%
42 - Wholesale Trade	1,280,032	17,196	875	98.6%	1.3%	0.1%
441 - Motor Vehicle and Parts Dealers	1,295,983	9,693	29	99.3%	0.7%	0.0%
442 - Furniture and Home Furnishings Stores	324,729	434	62	99.8%	0.1%	0.0%
443 - Electronics and Appliance Stores	660,228	413	11	99.9%	0.1%	0.0%
444 - Building Material and Garden Equipment and Supplies Dealers	1,339,121	3,891	8	99.7%	0.3%	0.0%
445 - Food and Beverage Stores	1,580,339	2,752	156	99.8%	0.2%	0.0%
446 - Health and Personal Care Stores	1,370,651	5,786	32	99.6%	0.4%	0.0%
447 - Gasoline Stations	383,477	449	582	99.7%	0.1%	0.2%
448 - Clothing and Clothing Accessories Stores	1,838,975	3,166	84	99.8%	0.2%	0.0%
451 - ”Sporting Goods, Hobby, Book, and Music Stores”	801,183	12,043	64	98.5%	1.5%	0.0%
452 - General Merchandise Stores	3,730,762	3,214	606	99.9%	0.1%	0.0%
453 - Miscellaneous Store Retailers	979,777	5,288	116	99.5%	0.5%	0.0%
454 - Nonstore Retailers	458,809	4,240	203	99.0%	0.9%	0.0%
481 - Air Transportation	273,811	1,381	44	99.5%	0.5%	0.0%
482 - Rail Transportation	66,015	11,662	418	84.5%	14.9%	0.5%
483 - Water Transportation	32,239	297	18	99.0%	0.9%	0.1%
484 - Truck Transportation	3,135,767	22,411	466	99.3%	0.7%	0.0%
485 - Transit and Ground Passenger Transportation	107,803	64,296	28	62.6%	37.4%	0.0%
486 - Pipeline Transportation	50,036	2,426	7,733	83.1%	4.0%	12.8%
487 - Scenic and Sightseeing Transportation	948	29	0	97.0%	3.0%	0.0%
488 - Support Activities for Transportation	222,317	2,060	338	98.9%	0.9%	0.2%
491 - Postal Service	41,827	225	0	99.5%	0.5%	0.0%
492 - Couriers and Messengers	494,113	37,468	47	92.9%	7.0%	0.0%
493 - Warehousing and Storage	88,641	612	30	99.3%	0.7%	0.0%
51 - Information	5,124,341	27,940	9,484	99.3%	0.5%	0.2%
52 - Finance and Insurance	11,360,815	24,748	1,759	99.8%	0.2%	0.0%
53 - Real Estate and Rental and Leasing	2,650,165	24,766	580	99.1%	0.9%	0.0%
54 - ”Professional, Scientific, and Technical Services”	12,387,922	154,572	14,101	98.7%	1.2%	0.1%
55 - Management of Companies and Enterprises	221,745	2,066	98	99.0%	0.9%	0.0%
56 - Administrative and Support and Waste Management and Remediation Services	7,359,522	70,788	3,822	99.0%	1.0%	0.1%
61 - Educational Services	8,312,462	91,904	620	98.9%	1.1%	0.0%
62 - Health Care and Social Assistance	21,620,327	42,922	5,645	99.8%	0.2%	0.0%
71 - ”Arts, Entertainment, and Recreation”	1,141,376	8,114	245	99.3%	0.7%	0.0%
72 - Accommodation and Food Services	9,169,235	63,964	1,424	99.3%	0.7%	0.0%
81 - Other Services (except Public Administration)	2,480,178	32,245	582	98.7%	1.3%	0.0%
92 - Public Administration	4,460,420	87,344	3,244	98.0%	1.9%	0.1%

Table 13: Evolution of the share of low-carbon ads, 2010-2012 vs 2017-2019

	All	Low skilled	High skilled
2017-19 vs 2010-12	0.000	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
Constant	0.014***	0.010***	0.004***
	(0.000)	(0.000)	(0.000)
Observations	1.416	1.416	1.416
R^2	0	0.01	0.05

Notes: We obtain the distribution of the share of low-carbon ads across commuting zones by year and low (high) skilled occupations. Table 13 regresses this low-carbon share on a dummy indicator for the period 2017-2019, contrasting with the 2010-2012 baseline for (1) All occupations; (2) Low skilled occupations and (3) High skilled occupations. Thus, a coefficient of 0.001 in column (2) indicates that the share of low-carbon ads in low-skilled occupations was 0.1% higher in 2017-2019 than in 2010-2012.

Table 14: Evolution of in selected SOC groups, 2010-2012 vs 2017-2019

	13-1	17-1	17-2	17-3	19-2	47	49	53
2017-19 vs 2010-12	−0.015***	−0.008**	−0.013***	−0.003	−0.008	0.008***	0.007***	−0.001
	(0.001)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.001)	(0.003)
Constant	0.035***	0.054***	0.053***	0.040***	0.096***	0.040***	0.023***	0.079***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.007)	(0.002)	(0.001)	(0.003)
Observations	845	338	1.062	889	639	1.082	1.197	1.267
R^2	0.13	0.01	0.08	0	0	0.03	0.06	0

Notes: Table 14 applies the same approach as Table 13 in each of the SOC groups we focus on in the present article. For reference: 13-1 - Business Operations Specialists; 17-1 - Architects, Surveyors, and Cartographers; 17-2 - Engineers; 17-3 - Engineering and Mapping Technicians; 19-2 - Physical Scientists; 47 - Construction and Extraction; 49 - Installation, Maintenance, and Repair; 53 - Transportation and Material Moving.

Spatial correlation between low and high carbon vacancies and income levels

Table 15: Correlation between the share of low-carbon ads and annual personal income

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(inc_{cz})$	0.006***	0.002*	0.002**
	(0.001)	(0.001)	(0.001)
Observations	685	685	685
R2	0.03	0.01	0.02
AIC	−4.974	−4.960	−4.961

Notes: Table 15 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. Standard errors clustered by CZ are provided in parentheses.

Table 16: 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***	−0.001**	−0.001***
	(0.002)	(0.000)	(0.000)
Observations	647	647	647
R2	0.03	0.01	0.01
AIC	−4.522	−4.456	−4.459

Notes: Table 16 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. Standard errors clustered by CZ are provided in parentheses.

Table 17: Correlation between the share of low and high carbon ads

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(1+s_{hc,cz})$	0.122**	0.065	0.067
	(0.057)	(0.045)	(0.052)
Observations	650	650	646
R2	0.02	0.00	0.00
AIC	−4.760	−4.757	−4.728

Notes: Table 17 presents estimates of $\beta_{lc,hc}$ in $\log(1+s_{lc,cz}) = \beta_{lc,hc}\log(1+s_{hc,cz}) + \varepsilon_{cz}$. $s_{lc,cz}$ is the average share of low-carbon ads in low skilled occupations between 2010 and 2019 in each CZ. $s_{hc,cz}$ is the average share of high carbon ads in low skilled occupations 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. Standard errors clustered by CZ are provided in parentheses.

Table 18: Correlation between the share of low-carbon ads and high carbon employment

	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(1+s^{emp}_{hc,cz})$	0.096***	0.020	0.017
	(0.028)	(0.020)	(0.022)
Observations	687	687	685
R2	0.03	0.00	0.00
AIC	−5.011	−4.996	−4.981

Notes: Table 18 presents estimates of $\beta^{emp}_{lc,hc}$ in $\log(1 + s_{lc,cz}) = \beta^{emp}_{lc,hc} \log(1 + s^{emp}_{hc,cz}) + \varepsilon_{cz}$. $s_{lc,cz}$ is the average share of low-carbon ads in low skilled occupations between 2010 and 2019 in each CZ. $s^{emp}_{hc,cz}$ 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. Standard errors clustered by CZ are provided in parentheses.

Table 19: 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 19 presents the Locational Gini for share of low-carbon ads per CZ, share of high carbon employment per CZ, share of high carbon ads per CZ and share of Construction & Extraction ads (SOC 47) per CZ. The Gini locational coefficient is calculated following (*48*) using our own job ads dataset and data on employment by occupation and commuting zone from the American Community Survey adapted from (*28*). 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 = US 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 20: Top low-carbon job identifiers by state

State	Most freq. low carbon	2^{nd} most freq.	3^{rd} most freq.
Alabama	Insulation	Bus Driving	Energy Conservation
Alaska	Insulation	Bus Driving	Pollution Control
Arizona	Bus Driving	Insulation	Renewable Energy
Arkansas	Insulation	Bus Driving	Energy Efficiency
California	Energy Efficiency	Renewable Energy	Bus Driving
Colorado	Renewable Energy	Energy Efficiency	Insulation
Connecticut	Energy Efficiency	Bus Driving	Insulation
Delaware	Bus Driving	Insulation	Energy Efficiency
Florida	Insulation	Energy Conservation	Bus Driving
Georgia	Insulation	Energy Conservation	Bus Driving
Hawaii	Bus Driving	Energy Conservation	Renewable Energy
Idaho	Clean Energy	Bus Driving	Insulation
Illinois	Bus Driving	Energy Efficiency	Insulation
Indiana	Insulation	Bus Driving	Energy Efficiency
Iowa	Ethanol	Insulation	Bus Driving
Kansas	Bus Driving	Insulation	Environmental Sustainability
Kentucky	Insulation	Bus Driving	Solar Panels
Louisiana	Insulation	Energy Efficiency	Energy Conservation
Maine	Bus Driving	Insulation	Renewable Energy
Maryland	Insulation	Energy Efficiency	Bus Driving
Massachusetts	Energy Efficiency	Renewable Energy	Energy Conservation
Michigan	Bus Driving	Fuel Efficiency	Insulation
Minnesota	Bus Driving	Insulation	Energy Conservation
Mississippi	Insulation	Energy Efficiency	Bus Driving
Missouri	Bus Driving	Insulation	Energy Conservation
Montana	Bus Driving	Insulation	Energy Conservation
Nebraska	Insulation	Ethanol	Bus Driving
Nevada	Bus Driving	Energy Conservation	Insulation
New Hampshire	Bus Driving	Insulation	Energy Efficiency
New Jersey	Bus Driving	Energy Efficiency	Insulation
New Mexico	Bus Driving	Insulation	Renewable Energy
New York	Energy Efficiency	Renewable Energy	Bus Driving
North Carolina	Insulation	Bus Driving	Energy Efficiency
North Dakota	Insulation	Wind Power	Wind Turbines
Ohio	Insulation	Bus Driving	Energy Efficiency
Oklahoma	Insulation	Bus Driving	Energy Efficiency
Oregon	Energy Efficiency	Bus Driving	Insulation
Pennsylvania	Bus Driving	Insulation	Energy Efficiency
Rhode Island	Bus Driving	Insulation	Energy Efficiency
South Carolina	Insulation	Bus Driving	Energy Conservation
South Dakota	Ethanol	Bus Driving	Insulation
Tennessee	Insulation	Energy Conservation	Energy Efficiency
Texas	Insulation	Bus Driving	Energy Efficiency
Utah	Energy Conservation	Insulation	Bus Driving
Vermont	Bus Driving	Energy Efficiency	Insulation
Virginia	Insulation	Energy Efficiency	Bus Driving
Washington	Insulation	Energy Efficiency	Bus Driving
West Virginia	Insulation	Bus Driving	Clean Air Act
Wisconsin	Bus Driving	Insulation	Energy Efficiency
Wyoming	Efficient Transportation	Insulation	Bus Driving

Skill gap

Table 21: Skill gap

	Cognitive		IT		Management		Social		Technical	
	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%

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 22: Skill gap magnitude across commuting zones

(a) Extensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	1.30% *	-0.30%	0.50%	-0.10%	5.10% ***
17-1 - Architects, Surveyors, and Cartographers	5.50% ***	13.90% ***	7.10% ***	4.10% ***	11.20% ***
17-2 - Engineers	1.70% ***	3.10% ***	5.50% ***	5.00% ***	4.20% ***
17-3 - Engineering and Mapping Technicians	4.40% ***	3.80% ***	10.80% ***	8.90% ***	9.10% ***
19-2 - Physical Scientists	2.80% ***	2.70% ***	6.80% ***	2.50% ***	7.20% ***
47 - Construction and Extraction	4.00% ***	6.10% ***	6.70% ***	3.90% ***	1.40% ***
49 - Installation, Maintenance, and Repair	-0.60% *	3.20% ***	11.60% ***	8.20% ***	11.70% ***
53 - Transportation and Material Moving	0.20%	0.10%	0.40%	7.10% ***	3.10% ***
b) High carbon vs Generic ads					
17-2 - Engineers	-1.40% *	1.70% ***	3.90% ***	3.20% ***	1.30% *
47 - Construction and Extraction	8.30% ***	6.00% ***	2.80% ***	8.50% ***	2.00% ***
c) Low carbon vs High carbon ads					
17-2 - Engineers	3.10% ***	1.30% **	1.60% **	1.80% **	2.90% ***
47 - Construction and Extraction	-4.40% ***	0.10%	4.00% ***	-4.70% ***	-0.60%

(b) Intensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	1.30% **	-1.20% *	6.50% ***	5.70% ***	6.90% ***
17-1 - Architects, Surveyors, and Cartographers	8.00% ***	-7.10% ***	12.50% ***	14.70% ***	10.30% ***
17-2 - Engineers	0.80% **	-1.70% *	7.60% ***	5.20% ***	8.30% ***
17-3 - Engineering and Mapping Technicians	2.20% ***	5.30% ***	7.10% ***	8.10% ***	8.00% ***
19-2 - Physical Scientists	-3.50% ***	8.20% ***	20.10% ***	6.90% ***	4.90% ***
47 - Construction and Extraction	0.70% ***	1.70% ***	2.30% ***	8.20% ***	2.40% ***
49 - Installation, Maintenance, and Repair	0.60% ***	1.40% ***	1.90% ***	5.10% ***	2.30% ***
53 - Transportation and Material Moving	0.20% **	0.30% **	0.30% **	2.80% ***	0.30% ***
b) High carbon vs Generic ads					
17-2 - Engineers	-1.40% ***	-10.70% ***	0.20%	-0.10%	2.60% **
47 - Construction and Extraction	0.80% ***	10.00% ***	1.60% ***	4.80% ***	0.20%
c) Low carbon vs High carbon ads					
17-2 - Engineers	2.20% ***	9.00% ***	7.40% ***	5.30% ***	5.70% ***
47 - Construction and Extraction	0.00%	-8.30% ***	0.80% **	3.50% ***	2.20% ***

Notes: Similarly to Table 21, 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 . 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 corresponding 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 23: Difference in skill gap between 2010-2012 and 2017-2019, across commuting zones

(a) Extensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	2.10% **	3.30% ***	1.40%	1.80% **	0.00%
17-1 - Architects, Surveyors, and Cartographers	-2.70%	2.30%	-0.50%	-3.10%	2.80%
17-2 - Engineers	-1.90% ***	0.10%	-1.50% **	3.40% ***	3.20% ***
17-3 - Engineering and Mapping Technicians	0.40%	1.70% *	1.30%	2.70% **	5.90% ***
19-2 - Physical Scientists	-0.80%	0.70%	-2.00%	-2.90% *	1.60%
47 - Construction and Extraction	2.00% ***	-2.00% ***	-5.80% ***	-1.50% *	-1.60% **
49 - Installation, Maintenance, and Repair	-2.30% ***	-0.80% *	-6.80% ***	-3.10% ***	-5.10% ***
53 - Transportation and Material Moving	-1.10% **	0.80% ***	-0.40%	6.10% ***	0.30%
b) High carbon vs Generic ads					
17-2 - Engineers	-1.20%	-2.10% *	-2.20%	-2.00% *	-2.00% *
47 - Construction and Extraction	-1.30% **	-2.40% ***	-4.20% ***	-1.80% ***	-3.40% ***
c) Low carbon vs High carbon ads					
17-2 - Engineers	-0.70%	2.20% *	0.70%	5.40% ***	5.20% ***
47 - Construction and Extraction	3.20% ***	0.40%	-1.50%	0.30%	1.80% **

(b) Intensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
13-1 - Business Operations Specialists	1.10% **	5.20% ***	2.40% ***	7.40% ***	0.80%
17-1 - Architects, Surveyors, and Cartographers	9.80% ***	0.20%	0.50%	3.80% *	0.80%
17-2 - Engineers	-0.40%	-3.70% ***	0.50%	2.20% ***	2.70% ***
17-3 - Engineering and Mapping Technicians	-1.20% **	-0.10%	-1.50%	1.80%	-1.60%
19-2 - Physical Scientists	2.30% **	-1.90%	4.40% ***	1.40%	0.80%
47 - Construction and Extraction	-0.70% ***	-0.90% **	-2.80% ***	0.10%	-1.30% **
49 - Installation, Maintenance, and Repair	-3.50% ***	-2.50% ***	-0.90% ***	9.70% ***	-3.40% ***
53 - Transportation and Material Moving	0.10%	-0.70% ***	-1.00% ***	2.80% ***	-0.40% ***
b) High carbon vs Generic ads					
17-2 - Engineers	0.90%	-0.10%	6.20% ***	0.00%	0.10%
47 - Construction and Extraction	-1.00% ***	6.90% ***	-0.90%	-3.30% ***	-0.70% **
c) Low carbon vs High carbon ads					
17-2 - Engineers	-1.40%	-3.60% **	-5.70% ***	2.20%	2.60% *
47 - Construction and Extraction	0.20%	-7.80% ***	-1.90% **	3.50% ***	-0.60%

Notes: We now turn to the evolution of the skill gap between job categories over time. We implement the approach described in Table 22 to compute the distribution of the skill gap between pairs of job categories across commuting zones in the periods 2010-12 and 2017-19. We then compare its evolution over time by regressing the skill gap over an indicator variable valued at 0 for the years 2010-12 and 1 over 2017-19. Thus a positive (resp. negative) value indicates a reduction (resp. increase) in the skill gap over time.

Wage gap

Table 24: Wage gap robustness

	Main specification				Control for degree				Control for industry			
	Weighted		Unweighted		Weighted		Unweighted		Weighted		Unweighted	
	2010-2012	2017-2019	2010-2012	2017-2019	2010-2012	2017-2019	2010-2012	2017-2019	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	0.027	0.047**	0.026	0.042**	0.080***	0.087***	0.083***	0.073**
	(0.017)	(0.022)	(0.019)	(0.020)	(0.026)	(0.017)	(0.023)	(0.015)	(0.025)	(0.030)	(0.027)	(0.027)
Total ads	237,257	716,067	237,257	716,067	123,559	429,527	123,559	429,527	115,215	318,274	115,215	318,274
Low carbon ads	3,048	7,855	3,048	7,855	1,735	4,273	1,735	4,273	1,613	3,686	1,613	3,686
R2	0.204	0.218	0.195	0.209	0.255	0.267	0.250	0.265	0.225	0.237	0.225	0.236
17-1 - Architects, Surveyors, and Cartographers												
Job ad is low carbon	-0.241***	-0.087*	-0.247***	-0.101	-0.185***	-0.093***	-0.188***	-0.094**	-0.178***	-0.073**	-0.153**	-0.079**
	(0.021)	(0.035)	(0.013)	(0.050)	(0.022)	(0.014)	(0.005)	(0.020)	(0.016)	(0.016)	(0.042)	(0.021)
Total ads	6,122	18,958	6,122	18,958	2,714	10,815	2,714	10,815	3,073	8,072	3,073	8,072
Low carbon ads	238	678	238	678	161	483	161	483	123	308	123	308
R2	0.355	0.216	0.394	0.254	0.414	0.250	0.468	0.304	0.416	0.258	0.458	0.290
17-2 - Engineers												
Job ad is low carbon	0.023*	-0.043*	0.017	-0.038	0.030*	-0.013**	0.019	-0.006	-0.029*	-0.018*	-0.034**	-0.008
	(0.013)	(0.020)	(0.013)	(0.025)	(0.017)	(0.005)	(0.016)	(0.009)	(0.017)	(0.010)	(0.014)	(0.016)
Total ads	138,328	205,682	138,328	205,682	91,005	149,391	91,005	149,391	52,030	80,412	52,030	80,412
Low carbon ads	7,287	10,057	7,287	10,057	5,556	7,614	5,556	7,614	3,402	4,899	3,402	4,899
R2	0.137	0.104	0.143	0.106	0.102	0.112	0.108	0.112	0.164	0.149	0.161	0.153
17-3 - Engineering and Mapping Technicians												
Job ad is low carbon	0.130***	0.038***	0.109***	0.041***	0.104**	0.031	0.079***	0.031	0.102***	0.031**	0.094***	0.033**
	(0.030)	(0.008)	(0.022)	(0.010)	(0.038)	(0.020)	(0.025)	(0.019)	(0.022)	(0.011)	(0.018)	(0.011)
Total ads	83,875	199,662	83,875	199,662	39,976	104,238	39,976	104,238	32,773	69,193	32,773	69,193
Low carbon ads	1,732	3,745	1,732	3,745	1,034	2,337	1,034	2,337	791	1,790	791	1,790
R2	0.185	0.140	0.204	0.159	0.312	0.231	0.335	0.258	0.280	0.205	0.293	0.223
19-2 - Physical Scientists												
Job ad is low carbon	0.071***	-0.029	0.071***	-0.011	0.048	0.006	0.050**	0.014	0.070***	0.032	0.070***	0.045
	(0.004)	(0.021)	(0.008)	(0.038)	(0.027)	(0.016)	(0.020)	(0.026)	(0.013)	(0.021)	(0.010)	(0.029)
Total ads	16,775	25,707	16,775	25,707	10,994	18,955	10,994	18,955	10,416	13,912	10,416	13,912
Low carbon ads	1,151	2,473	1,151	2,473	836	1,909	836	1,909	700	1,195	700	1,195
R2	0.249	0.191	0.254	0.213	0.265	0.230	0.272	0.252	0.293	0.250	0.284	0.259
47 - Construction and Extraction												
Job ad is low carbon	0.044	-0.021*	0.040	-0.014	-0.013	-0.002	0.011	0.006	0.065	-0.013	0.064	-0.004
	(0.053)	(0.012)	(0.038)	(0.011)	(0.029)	(0.018)	(0.025)	(0.017)	(0.061)	(0.021)	(0.046)	(0.016)
Total ads	98,200	269,768	98,200	269,768	22,389	65,878	22,389	65,878	41,870	120,945	41,870	120,945
Low carbon ads	3,976	13,261	3,976	13,261	1,263	4,347	1,263	4,347	1,956	5,956	1,956	5,956
R2	0.267	0.291	0.256	0.264	0.359	0.419	0.349	0.386	0.294	0.270	0.296	0.255
49 - Installation, Maintenance, and Repair												
Job ad is low carbon	0.067***	0.040***	0.050*	0.035***	0.085***	0.042***	0.067**	0.043***	0.039	0.018	0.008	0.030*
	(0.025)	(0.006)	(0.030)	(0.009)	(0.019)	(0.005)	(0.029)	(0.009)	(0.049)	(0.014)	(0.060)	(0.017)
Total ads	213,923	567,184	213,923	567,184	73,780	235,624	73,780	235,624	104,123	285,440	104,123	285,440
Low carbon ads	5,757	15,376	5,757	15,376	2,411	6,651	2,411	6,651	3,155	8,439	3,155	8,439
R2	0.149	0.133	0.172	0.163	0.263	0.202	0.284	0.237	0.197	0.156	0.240	0.195
53 - Transportation and Material Moving												
Job ad is low carbon	0.157***	-0.064*	0.108*	-0.030	-0.044	0.202***	-0.033	0.154***	-0.098	-0.100***	-0.005	-0.046
	(0.045)	(0.034)	(0.063)	(0.037)	(0.078)	(0.015)	(0.033)	(0.038)	(0.059)	(0.022)	(0.066)	(0.044)
Total ads	349,336	1,489,698	349,336	1,489,698	74,384	282,924	74,384	282,924	151,313	652,591	151,313	652,591
Low carbon ads	10,155	35,860	10,155	35,860	4,149	17,915	4,149	17,915	8,124	26,236	8,124	26,236
R2	0.359	0.394	0.341	0.388	0.261	0.288	0.334	0.299	0.410	0.370	0.401	0.400
17-2 - Engineers												
Job ad is high carbon	0.239***	0.074***	0.201***	0.049**	0.176***	0.049*	0.145***	0.021	0.219***	0.061***	0.190***	0.041**
	(0.029)	(0.017)	(0.047)	(0.020)	(0.013)	(0.025)	(0.025)	(0.025)	(0.047)	(0.012)	(0.046)	(0.017)
Total ads	138,328	205,682	138,328	205,682	91,005	149,391	91,005	149,391	52,030	80,412	52,030	80,412
High carbon ads	2,802	1,703	2,802	1,703	1,817	1,216	1,817	1,216	1,577	1,123	1,577	1,123
R2	0.139	0.104	0.144	0.105	0.103	0.112	0.109	0.112	0.167	0.150	0.163	0.153
47 - Construction and Extraction												
Job ad is high carbon	0.202**	0.161***	0.152*	0.094	0.156*	0.099**	0.233***	0.114***	0.183**	0.133***	0.150*	0.064
	(0.077)	(0.046)	(0.085)	(0.058)	(0.085)	(0.046)	(0.072)	(0.039)	(0.080)	(0.037)	(0.083)	(0.057)
Total ads	98,200	269,768	98,200	269,768	22,389	65,878	22,389	65,878	41,870	120,945	41,870	120,945
High carbon ads	3,018	6,822	3,018	6,822	1,028	3,078	1,028	3,078	1,597	3,907	1,597	3,907
R2	0.267	0.291	0.256	0.264	0.360	0.419	0.350	0.386	0.295	0.271	0.296	0.255
Fixed effects												
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6-digits SOC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No

Table 25: 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	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
17-1 - Architects, Surveyors, and Cartographers									
Generic	220,494	9.9	7.8	13.0	6.2	5.5	3.2	61,833	32,227
Low carbon	10,473	15.4	7.9	14.2	4.6	5.1	3.5	60,217	26,033
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
53 - Transportation and Material Moving									
Generic	10,793,119	2.9	3.5	6.7	6.1	2.1	2.2	49,595	38,542
Low carbon	201,256	4.7	4.5	9.3	5.1	2.4	2.1	40,273	29,481

	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	1,430,951	10.3	7.2	-0.849***	12.2	6.4	-1.42***	3.2	2.4	-0.574***	51,907	28,456
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
17-1 - Architects, Surveyors, and Cartographers												
Generic	37,012	10.0	7.8	0.0913**	12.0	6.8	-1.04***	4.5	2.9	-0.99***	61,833	32,227
Low carbon	1,463	15.9	8.2	0.488**	13.6	5.5	-0.585***	4.4	3.1	-0.734***	60,217	26,033
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
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
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
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
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
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
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
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
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
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
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
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
53 - Transportation and Material Moving												
Generic	3,146,085	2.6	3.0	-0.352***	4.9	6.0	-1.82***	2.2	2.2	0.0705***	49,595	38,542
Low carbon	72,108	4.7	4.8	0.0168	8.8	5.4	-0.51***	2.3	2.2	-0.0805***	40,273	29,481