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Skills and wage gaps in the low-carbon transition: comparing job vacancy data from the US and UK

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Summary

Key findings

- Low-carbon jobs are systematically more skills-intensive than other jobs.
- Across the US and UK, low-carbon jobs have greater requirements for technical, managerial and social skills compared with other jobs. Low-carbon jobs require higher-level IT and cognitive skills too, which are also in high demand due to the ongoing digital transformation.
- The emerging skill gap resulting from the low-carbon transition is therefore larger and broader than previously considered.
- While high-carbon manual jobs are extremely spatially concentrated around centres of fossil fuel extraction, low-carbon vacancies are more dispersed in both the US and UK. This is true for both high- and low-skill occupations.
- In the UK, low-carbon jobs are concentrated in occupations that pay higher wages but exploring the wage gap within narrowly defined occupational groups reveals there has been a shift over the last decade. In the earlier half of the 2010s, low-carbon jobs paid a positive wage premium of up to 15% in most occupations but in the most recent data, a wage gap between low-carbon and similar generic jobs has largely eroded in both the US and UK.
- The lack of a positive wage premium in recent years despite these jobs having higher skill requirements is problematic for attracting workers into low-carbon jobs.

Research context

- As governments worldwide increase their commitments to tackling climate change, the number of low-carbon jobs is expected to grow rapidly. However, precisely what constitutes a 'low-carbon job' and their characteristics remains poorly understood, in part due to the lack of agreed definitions and measures of such jobs, especially outside the United States.
- This report summarises research characterising low-carbon jobs in the US by Saussay et al. (2022) and extends this by including and comparing with new results for the UK.
- The research develops a new approach to identifying low-carbon jobs based on the task content of jobs and comprehensive online job posting data. This method enables direct comparisons between low-carbon jobs and very similar non-low-carbon jobs to reveal unique characteristics of low-carbon jobs in terms of wages, skills and localisation.
- Unlike previous analyses conducting cross-occupation comparisons based on the green task content of jobs (Vona et al., 2018), our approach measures how low-carbon jobs differ from very similar jobs at a very disaggregated level. For example, the skill and wage gap between an automotive engineer working on electric vehicles versus one working on conventional cars can be precisely quantified. This provides policymakers with information on very specific skill gaps that could be closed by targeted retraining policies.

Are low-carbon jobs on the rise?

- In both the US and UK, low-carbon jobs constitute a relatively small share of jobs advertised, averaging 1.4% in the UK between 2012 and 2021, and 1.35% in the US between 2010 and 2019. In the UK in 2022, 1.4% of the workforce equated to around 490,000 workers. While these shares appear small, they are significantly larger than the share of jobs in high-carbon extraction sectors.

- In the UK, the share of low-carbon jobs being advertised declined significantly from 1.8% in 2012 to 1.1% in 2018. This trend coincided with removal of funding for various supply- and demand-side energy schemes from 2012/2013 and the decline in broader climate policies during this period. Since then, low-carbon job advertisement shares increased to 1.6% in 2021.
- In the US, in contrast to the general rise in renewable power production jobs, the share of overall low-carbon vacancies in total online job vacancies was fairly steady over the period 2010 to 2019. However, trends over that decade diverged between high-skill occupations (such as managers or engineers), which declined from 0.36% to 0.30% of low-carbon job ads, and low-skill occupations (such as manual workers), which grew from 0.97% to 1.12%. These trends correspond to the job creation effect of green American Recovery and Reinvestment Act (ARRA) spending (Popp et al., 2021), which was concentrated in manual occupations. This suggests that green recovery plans could help to offset deterioration of labour market conditions for unskilled workers.

Skill requirements of low-carbon jobs

- Across both the US and UK, low-carbon job vacancies are more likely than non-low-carbon jobs to require wide-ranging key skills, namely technical, managerial, social, cognitive and IT. This suggests low-carbon jobs are systematically more skills-intensive than other jobs. Finding similar results in the US and UK suggests that we are uncovering something inherent about the skill profile of low-carbon jobs, and measuring the 'intrinsic' low-carbon skill gap.
- In particular, across the US and UK, low-carbon jobs have greater requirements for technical, managerial and social skills compared with other jobs. Low-carbon jobs require higher-level IT and cognitive skills too, which are also in high demand due to the ongoing digital transformation. The emerging skill gap resulting from the low-carbon transition is therefore larger and broader than previously considered in the cross-occupational analysis for the US (Vona et al., 2019).
- High-carbon job vacancies are systematically more skills-intensive than low-carbon jobs in the US, but not in the UK, where this is the case only for high-skill occupations. In the UK, displaced high-carbon workers in low-skill occupations will be hampered by a similar lack of necessary skills to those in generic jobs.
- There are important differences across occupational groups regarding skill gaps and reskilling requirements. In some occupations such as engineering, transitioning to a low-carbon activity involves an expansion of skills or further specialisation in skillsets that are already core to that occupation. In other occupations such as business managers, the transition to low-carbon activities instead requires a diversification of skills, in other words, acquiring skills not currently part of the core skillset required in that occupation. Finding retraining solutions will therefore likely need to be tailored to meet the specific needs of occupations affected by decarbonisation, or of the companies hiring these workers.

In which geographical and sectoral areas are low-carbon jobs increasing?

- One of the key challenges in delivering a 'just transition' and thereby maintaining crucial public support for net zero is to ensure that displaced workers in energy- or pollution-intensive industries, particularly those in low-skill (mostly manual) occupations, find new jobs with similar pay and working conditions.
- Across all skill groups, the areas of the UK with the highest low-carbon share of vacancies are located away from South East England. The Greater London area has a high number of low-carbon vacancies but they represent a relatively small share of the overall labour market.

These patterns provide some evidence to suggest that the low-carbon transition can provide regionally-balanced economic opportunities in the UK.

- High-carbon manual jobs are spatially concentrated around centres of coal, crude oil, gas, and shale oil and gas extraction. In the UK these jobs are located close to the North Sea, while in the US they are in areas including Wyoming, West Virginia, Oklahoma, Texas and the Appalachian region.
- In contrast, low-carbon vacancies are more dispersed in both the US and UK. This is true for both high-skill (e.g. engineering and science) and low-skill (e.g. buildings and transport) occupations.
- Renewable energy is an exception, where unlike buildings and transport, job ads are more spatially concentrated, reflecting natural resource endowment. In the UK, a higher concentration of low-carbon job ads is found across Scotland, and the North West and South West regions of England, reflecting this spatial concentration of jobs in renewables. In the US, there are higher low-carbon job shares in areas with high solar (e.g. California and Nevada) and wind power potential (e.g. the Minnesota–Texas wind corridor).
- In both the US and UK, the geographical overlap between low- and high-carbon jobs is limited for low-skill occupations. In contrast, in high-skill occupations in the UK, there is a positive spatial correlation between low- and high-carbon job ad shares, with a high share of both types of vacancy in Scotland. This suggests that the low-carbon transition could exacerbate existing regional inequalities in the US while in the UK the situation is less clear.

Wage premium – are low-carbon jobs better paid?

- In the UK, low-carbon jobs are concentrated in occupations that pay higher wages. However, looking within narrowly defined occupational groups reveals that there is not always a wage premium. For example, low-carbon finance jobs pay more than the average job or the average high-skill job, but may not pay more than the average finance job.
- Exploring the wage gap within narrowly defined occupational groups reveals there has been a shift over the last decade. In the most recent data, a wage gap between low-carbon and similar generic jobs has largely eroded compared with the earlier half of the 2010s, when low-carbon jobs paid a positive wage premium in most occupations of up to 15%. This shift is observed in both the US and UK.
- The general positive wage premium during the earlier period could suggest there was a skills shortage and/or concomitant wage growth or policy pass-through to compensate workers for meeting the higher skill requirements of low-carbon jobs.
- The lack of a positive wage premium in recent years despite these jobs having higher skill requirements is problematic for attracting workers to low-carbon jobs.
- There are some differences across occupations, however. In the UK, a positive low-carbon wage premium found in low-skill occupations such as in construction and building, or process, plant and machine operatives, could be indicative of several underlying drivers. These include a skills shortage, or higher value being placed on such jobs by the employers and the market (indicating higher productivity). Here the largest skill gaps are found in management, social and technical skills.
- High-carbon fossil fuel industry jobs in the UK are few in number and do not pay a wage premium. In contrast, in the US these jobs have experienced a boom, especially with the shale gas revolution, and pay a significant positive wage premium. These high-carbon workers will likely experience earning losses when moving to a generic job or a green job.

Policy implications

- Low-carbon jobs are different from similar non-low-carbon jobs in the same occupation. Low-carbon jobs are intrinsically more skills-intensive, especially for technical, social and managerial skills. Yet low-carbon jobs do not always pay higher wages than similar jobs within the same occupation, despite the higher skill requirements. Reconciling this gap is a neglected but important issue for managing the low-carbon transition.
- Public investment to retrain workers to narrow the low-carbon skill gap is therefore likely to help deliver a smooth, rapid and 'just' transition. Our results on skill gaps support previous findings from Popp et al. (2021) that green fiscal push policies including stimulus packages should include investments in retraining. Finding appropriate solutions to fill the skill gap in the transition is likely to require cooperation among industry, trade unions, industry associations, technical and vocational schools, and other social actors.
- The evidence from the combined US and UK analysis show that the low-carbon transition entails potentially high reallocation costs associated with both the reskilling of workers and the demands for regional labour mobility due to the location of low-carbon jobs, particularly for low-skill occupations.
- Reallocation costs associated with workers' reskilling and earning losses are often ignored when evaluating labour market impacts of environmental policies. The improved evidence base on reallocation costs should be used to calibrate integrated assessment and computational general equilibrium models used to assess macroeconomic impacts of climate change mitigation.
- The spatial patterns in the US and UK are different. Spatial inequalities induced by the low-carbon transition are likely to be greater in the US, where high-carbon jobs tend to be located in poorer areas while low-carbon jobs tend to be in richer areas. The impact of wage losses for high-carbon workers will be amplified by negative multiplier effects in affected communities. Whether the low-carbon transition could exacerbate existing regional inequalities in the UK is less clear. In the UK, the share of low-carbon vacancies tends to be higher in regions with higher unemployment and with lower productivity, especially for low-skill occupations. This suggests a need for a tailored policy response to suit local conditions, to ensure the adequate supply of skills and support for affected workers.
- In both the US and UK, low-carbon job creation rates over the last decade follow distinct national patterns and declines in the number of new jobs appear to coincide with the removal of targeted climate-related funding or programmes such as improving home energy efficiency. Further analysis is needed to assess the job creation effect of various policy interventions.

This research is the first to systematically identify and characterise low-carbon jobs using job vacancy data in the UK. Policymakers can use the approach using selected low-carbon key words, natural language processing techniques and job vacancy data developed by this research programme to monitor skill gaps associated with specific technologies and sectors that are relevant for a local economy, to improve the effectiveness and targeting of retraining programmes.

1. Introduction

Delivering climate neutrality, or 'net zero', by 2050, as both the United States and United Kingdom have pledged, requires a deep transformation of all economic sectors (Rockström et al., 2017). Emerging climate solution technologies, such as new methods of energy production or carbon dioxide removal, will add another layer to ongoing technological change, along with digitisation and Artificial Intelligence (Autor et al., 2003; Acemoglu and Autor, 2011). These parallel transitions are expected to significantly reshape the way we live and work.

The low-carbon transition will involve reallocating workers towards low-carbon activities while skills demanded by high-carbon activities may be lost as jobs are displaced. The political imperative of delivering jobs (Hanna et al., 2020) and supporting a 'just transition' that addresses the needs of workers and communities where there are high-carbon industries is a priority. Achieving such a transition will enhance the political acceptability of climate action (Vona, 2019), particularly in the post-COVID-19 context (Zhang et al., 2022), as is acknowledged for example in the Glasgow Climate Pact.

The transition raises some key policy questions, such as:

- What are low-carbon jobs?
- In which geographical regions are low-carbon jobs emerging?
- What skills are needed to fill these roles?
- Does the labour force have the required skillset to easily transition into low-carbon jobs?
- Will workers have to retrain or move to another region?
- Do low-carbon jobs pay a good wage?
- Can the low-carbon transition improve labour market conditions for low-skill workers to offset some of the impacts of the ongoing trends in automation and globalisation, and counteract rising aggregate inequality and job polarisation?
- What can be done to ensure workers in jobs at risk from the low-carbon transition are not left behind?

This report aims to answer some of these questions, providing a detailed characterisation of low-carbon jobs from the last decade in the US and the UK. It brings new evidence to support policy discussions. The report is written from a comparative perspective, drawing out the characteristics of low-carbon jobs in general, and aspects that are driven by distinctive national patterns. We summarise findings from a recent Grantham Research Institute working paper by Saussay et al. (2022) that uses online job vacancy data to develop a novel methodology to precisely identify low-carbon jobs and characterise the skill requirements and other attributes of low-carbon jobs in the US between 2010 and 2019. We then present and compare these findings with new results from a similar analysis on the UK carried out for the period 2012 to 2021.

Before we address this new method and describe the results of our analysis, below we outline some of the approaches used and broad findings to date.

Challenges in quantifying green jobs and any associated wage or skill gap

Much of the uncertainty around the labour market impacts of the low-carbon transition can be attributed to a basic problem in identifying the jobs. Until recently, these methodological challenges meant that identifying low-carbon jobs could not be done with a high degree of confidence. It has been common to conflate green jobs with those in traditional, core environmental sectors like water, sewage and waste collection, or with jobs associated with renewable electricity generation (as is discussed for example in Sulich et al., 2020). However, such a 'top-down' approach (or industry-level analysis) is not granular enough to be able to accurately capture low-carbon activity, plus it provides an incomplete definition because decarbonisation affects all corners of the economy.

Typically, low-carbon jobs emerge as the content of a job is altered with the adoption of new low-carbon technologies or cleaner methods of production. For example, more automobile engineers have to adapt to hybrid, electric or hydrogen technologies; or installation technicians start to implement new energy efficiency standards. Therefore the greening of jobs is happening within sectors and occupations. However, drawing out what is distinct about low-carbon jobs compared with similar non-low-carbon jobs in the same occupational group has been difficult to date.

Estimating the number of green jobs in the UK

Exemplifying the opacity of green jobs is the absence of standardised definitions or methods for measuring low-carbon jobs. A wide range of estimates have been produced on the low-carbon labour market share, often produced from high-level, top-down analyses. In the UK, sectoral analysis by the Office for National Statistics' (ONS) Low Carbon and Renewable Energy Economy Survey (LCREE) documents 207,800 full-time equivalent (FTE) jobs in 2020, with no significant change since 2014 (ONS, 2022). Most of this employment activity occurred within the manufacturing, energy supply and construction industries and equated to a 1% total share of non-financial employment in the UK (ibid.). The [erstwhile] Department for Business, Innovation and Skills (BIS) constructed a profile of the UK low-carbon economy constituting six sector groupings linked to decarbonisation between 2010 and 2013. Direct employment in 2013 was estimated at 1.6% with annual employment growth in the low-carbon economy estimated at 3.8% year on year (Graves et al., 2015). One more recent analysis uses UK job vacancy data, and finds that between July 2021 and July 2022, 2.2% of advertised jobs were green jobs (336,000 unique jobs), rising from 1.2% in 2020/2021 (PwC, 2022).

Estimating the wage premium in the US and UK

Evidence of whether there is a wage premium associated with green jobs has also been based on aggregate or occupational-level analyses. Muro et al. (2019) find that workers in clean energy jobs have mean hourly wages 8–19% higher than the US national average while workers in the lowest income brackets earn US$5–10/hour more than other entry-level jobs. For the UK, a snapshot of the green job wage premium in sectors within the LCREE finds the median wage for full-time employees in LCREE industries is 30% higher than the median wage in carbon-intensive industries (Christie-Miller and Luke, 2021).

Bottom-up, task-based approaches to quantifying green jobs and the wage premium

An alternative 'bottom-up' approach (or occupation- or task-specific analysis) could be taken to overcome issues associated with aggregate-level analysis and improve the measurement of low-carbon employment. For the US, this has involved combining insights from the task-based approach to labour markets (Autor et al., 2003; Acemoglu and Autor, 2011) with occupation-level data on task and skill requirements from the Green Economy Program of the Occupational Information Network (O*NET) (Vona et al 2015; Consoli et al., 2016; Vona et al., 2018; Bowen et al., 2018; Marin and Vona, 2019) to measure occupation-level exposure to green technologies and production. Using this approach, Vona et al. (2018) show that greener occupations rely heavily on technical and engineering skills to solve and implement solutions to specific environmental problems. Using a task-based rather than a binary measure of green job, i.e. based on the green task intensity of occupation, Vona et al. (2019) estimate that the share of green employment in the US ranges from 2–3%, which is in the ballpark of estimates obtained using green production as a proxy of green employment. Vona et al. (2019) also find that green jobs command a 4% wage premium on average relative to similar occupations. Interestingly, the wage premium is higher in low-skilled than in high-skilled occupations.

To apply this approach to the UK context, Valero et al. (2021) crosswalk[1] O*NET occupational classifications to the UK classification system and link these classifications to Labour Force Survey data to estimate the degree of 'greenness' of an individual's job. They estimate the share of green employment at 17% in 2019. Similar results are obtained by Robins et al. (2019), also using a cross-walking approach. These much larger estimates of the share of green employment compared, for example, with Vona et al. (2019) are likely due to two measurement issues. First, the UK studies do not use a task-based measure of green jobs. Thus, for instance, construction workers are considered as entirely green, while they are only 11% green using the task-based definition. Second, the imputation of US green jobs or tasks to the UK context creates a well-known aggregation problem because the UK occupational data are not as disaggregated as the US data (Vona et al. 2021).

Two studies estimate the green job wage premium with bottom-up approaches in the UK. Valero et al. (2021) find that British green jobs appear to be associated with a positive wage premium. This premium is most pronounced at lower skill levels, controlling for education and work experience. Taking a subset of more directly green jobs, Broome et al. (2022) find an 8% wage premium for UK green job workers, yet the share of high-carbon job workers moving to green jobs has been low, at 2.9% in 2019. Still, the occupational-level analyses lacks the granularity to be able to precisely isolate low-carbon jobs from non-low-carbon jobs within the same occupation. In general, the occupational-level analyses lacks granularity to precisely isolate low-carbon jobs from non-low-carbon jobs within the narrowly defined occupations.

1 A 'crosswalk' between classification systems is required when applying O*NET classifications to non-US contexts, connecting US occupational codes to the codes of the country being studied (Valero et al., 2021).

2. Identifying low-carbon jobs using data from advertised job vacancies: our approach

Overview of the method

Saussay et al. (2022) developed a methodology to accurately isolate low-carbon activities in online job vacancy data (from Lightcast, a labour market analytics company), combining natural language processing (NLP) and a survey of experts. Lightcast acquires raw text from online job advertisements (or 'ads') through extensive web scraping. It then extracts standardised variables, characterising them through a combination of NLP approaches. The resulting dataset covers the near-universe of online jobs, and provides many standardised variables, including for occupation, skills required, salary offered and education requirements. Using their skills taxonomy of over 16,000 skills, they extract from each job advertisement a list of skills requested by employers. These skills are not specifically labelled as low-carbon or high-carbon.

Using the data from Lightcast, Saussay et al. (2022) applied natural language techniques to select a set of valid low-carbon keywords from existing definitions of green tasks and products. These keywords were then mapped to a vector of skills contained for each job ad using semantic matching, a natural language processing technique, to assign a 'low-carbon matching score' for every skill. Ambiguous cases were resolved around the cut-off level through expert elicitation.

This procedure produced a list of 445 low-carbon skills that can be used as low-carbon job identifiers. An advertised job is considered low-carbon if it contains at least one low-carbon job identifier. As the Lightcast skills taxonomy varies slightly in the UK from the US, in the extension to the research presented here we have reapplied this methodology to the UK dataset and recover a further 23 low-carbon skills, for a total of 468 low-carbon identifiers.

This method is summarised in Figure 1 and detailed in Saussay et al. (2022).

Figure 1. Identifying low-carbon jobs using job ad data

	Action	Results	Examples
1. Collect online job ads data	Codify job ads text using Natural Language Processing techniques	16,000 keywords / skills	*Cash Handling, Exterior Painting* *Oil Mining, Problem Solving*
2. Identifying low-carbon keywords	Apply NLP (TF-IDF) to pre-existing green tasks (O*NET) and products (PRODCOM)	250 low-carbon keywords	*Photovoltaic, Insulation, Energy efficiency*
3. Mapping to Lightcast skills	Use semantic matching to match each skill with the 250 low carbon keywords	396 low-carbon job identifiers 600 ambiguous matches	*Wind Power, Photovoltaic (PV) Systems* *Energy Solutions, Air Pollution Control*
4. Expert survey	Resolve ambiguous matches via expert survey	49 additional low-carbon identifiers **445 low-carbon identifiers in total**	*Commercial Solar Sales, Cooling Efficiency* *Biomass, Energy Efficiency, Fuel Cell*

Source: Authors

Advantages and limitations of the method

This approach to identifying green jobs has several key advantages over previous methods. Above all, it allows for comparison of skills and salaries between green and non-green variants of the same occupation. This comparison is more salient than comparing across occupations since workers are more likely to transition towards low-carbon jobs within the same occupational group than to jobs outside it. Measuring within-occupation skill and salary gaps is therefore key to understanding labour market aspects of the low-carbon transition.

Furthermore, the methodology is transparent and flexible, and can be easily replicated in different country contexts. It offers a toolkit for both researchers and policymakers to design targeted retraining and reskilling policies within green deal packages.

It is important to note that online job vacancies capture changes in labour demand, rather than the aggregate employment stock. Compared with the aggregate employment population, the current flow of job demand over-represents growing firms (Davis et al., 2012).

Further, online job postings are biased against and towards different job types: some job types are not advertised online, including self-employment; other job types are heavily represented in online ads, including business and financial, computer and mathematical, and healthcare occupations; jobs that are under-represented in online ads include those in construction, public administration and government, mining and logging, and accommodation and food services (Lancaster et al., 2021). In our analyses, we partially restore representativeness by re-weighting low-carbon jobs using US Bureau of Labor Statistics employment shares (see Table 7.2, Appendix). One limitation of using job vacancy data is that it is not possible to directly assess existing low-carbon jobs, for example the characteristics of the workers holding these jobs.

Another important difference compared with previous approaches to identifying green jobs is that we focus on low-carbon activities. This analysis excludes traditionally 'green' activities such as water treatment and waste management. Estimates of low-carbon jobs using job vacancies in the UK in Saussay et al. (2022) remain, however, in the ballpark of previous estimates of the share of green jobs (Becker and Shadbegian, 2009; Elliott and Lindley, 2017; Vona et al., 2019; Popp et al., 2021) though on the lower end, due in part to the exclusion of non-climate-related environmental activities.

Table 1 provides a comparison between the US sample used in Saussay et al. (2022) and the new UK dataset described in this report.

Table 1. Comparison of US and UK samples

	United States	United Kingdom
Sample period	2010–2019	2012–2021
Occupational classifications	US SOC codes: 848 distinct occupations excluding the military Occupations typically split into high- and low-skill groups	UK SOC codes: 369 distinct occupations Occupations typically split into high-, middle- and low-skill groups
Industry classifications	NAICS	SIC 2007
Inclusion of salary information	22% of ads	62% of ads
Inclusion of degree and experience requirements	More inclusion	Less inclusion

Notes: SOC = Standard Occupational Classification. NAICS = North American Industry Classification System. SIC = Standard Industrial Classification.

Major occupational groups for low-carbon employment

Using low-carbon key words identifies low-carbon jobs across most sectors of the economy. In terms of occupations, **the 2-digit Standard Occupational Classification (SOC) groups with the highest shares of weighted low-carbon job ads in the UK are:**

- Transport and mobile machine drivers and operatives
- Skilled construction and buildings trade
- Process, plant and machine operatives
- Skilled metal, electrical and electronic trades
- Science, research, engineering and technology professionals
- Science, engineering and technology associate professionals (see Figure 7.7, Appendix).

These are similar to the major low-carbon SOC groups identified by Saussay et al. (2022) in the US – Business and finance; Architecture and engineering; Life, physical and social science; Construction and extraction; Installation, maintenance and repair; and transportation – and are also similar to the most green-task-intensive in the O*NET data (Vona et al., 2019), except for Business professionals, which are harder to identify in the UK SOC.

At the more disaggregated 3-digit SOC level, five high-skill occupational groups stand out:

- Natural and social science professionals
- Engineering professionals
- Architects, town planners and surveyors
- Science, engineering and production technicians
- Draughtspersons and related architectural technicians

These largely correspond to the high-skill 3-digit SOC occupations examined in Saussay et al. (2022), except again for Business operation specialists (see Table 7.1, Appendix). We examined the differences between low-carbon and generic jobs in these five 3-digit occupational groups. For middle- and low-skill occupations, we considered the four 2-digit SOC groups with a high intensity of low-carbon ads: Skilled metal, electrical and electronic trades; Skilled construction and building trades; Process, plant and machine operatives; Transport and mobile machine drivers and operatives. This is because worker mobility is higher for middle- and low-skill workers across 3-digit occupations than for high-skill workers. In the latter group, switching between 3-digit occupations requires substantial investment in formal education (e.g. from biology to physics).

Identifying high-carbon jobs in advertised vacancies

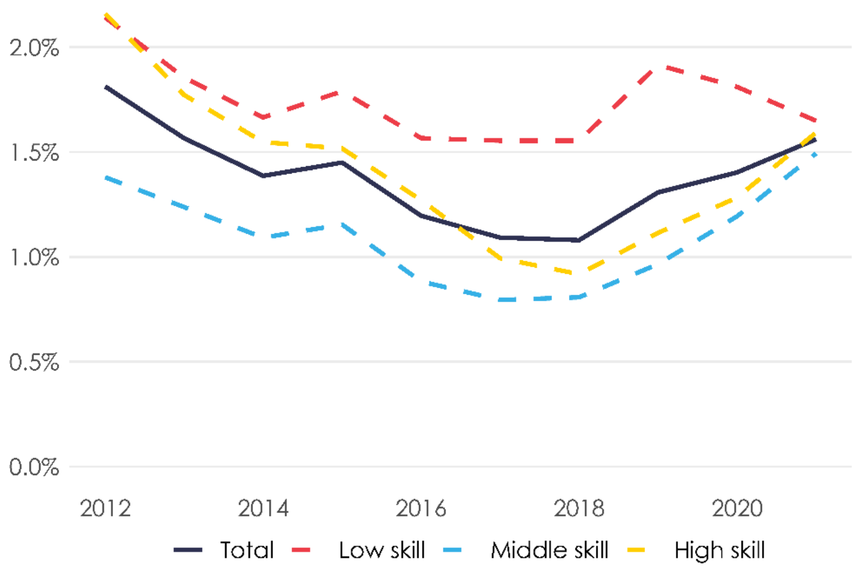
In contrast to low-carbon jobs, high-carbon jobs are relatively concentrated in well-established sectors and occupations. To identify high-carbon job ads in the Lightcast data we use a combination of occupation and industry: advertised jobs for extraction, construction and engineering occupations that are also in fossil fuel-related sectors are defined as high-carbon jobs. Note that this definition focuses on jobs that will unavoidably disappear due to the low-carbon transition, and does not include jobs in heavy industry, which (subject to industrial decarbonisation) are not necessarily at risk.

3. Are low-carbon jobs on the rise?

Aggregate trends

Our findings for the UK show an average share of total low-carbon job vacancies of 1.4% over the sample period of 2012–2021 (see Figure 2). This is over 17 times greater than the number of high-carbon jobs advertised in 2021 and roughly equivalent to the total number of persons employed in all mining and quarrying (SIC section B) in 2019 Q4 (Eurostat, 2022).

Figure 2. Evolution of low-carbon share of job ads, 2012-2021, UK



Notes: To obtain the low-carbon share of job ads, first we calculate the low-carbon share of job ads at the 4-digit SOC-level as the ratio of the number of low-carbon ads and the total number of ads in a given 4-digit occupation; next we take a weighted average of this ratio across occupations within each skill level grouping, using number of persons employed in each 4-digit occupation as weights. We obtain employment data from the ONS Labour Force Survey. High-skill occupations are those in SOC major groups 1 (Managers, directors, and senior officials), 2 (Professional occupations), and 3 (Associate professional and technical occupations); middle-skill occupations are in SOC major groups 4 (Administrative and secretarial occupations) and 5 (Skilled trades occupations); low-skill occupations are in SOC major groups 6 (Caring, leisure and other service occupations), 7 (Sales and customer service occupations), 8 (Process, plant and machine operatives), and 9 (Elementary occupations). Source: Authors.

There is considerable variation over time in the UK, in contrast to the US: in the UK the low-carbon job ad share declined from 1.8% in 2012 to 1.1% in 2018, and then increased again to 1.6% in 2021. While our analysis cannot attribute a causal link between these trends and policy developments, the decline in the earlier part of the sample period coincides with a decline in policy support for renewables and broader climate initiatives, and the increase more recently correlates with the Industrial Clean Growth Strategy in 2017, the Net Zero Commitment in 2019 and the Ten Point Plan in 2020.[2]

[2] Between 2010 and 2013 the Conservative Party climbed down from a series of high-profile and unpopular environmental policies e.g. plans to nationalise 15% of the national forestry estate, the proposed HS2 (high speed rail) route, a badger cull to control TB, and fracking (Carter and Clements, 2015). The rise in domestic energy prices in 2013 brought criticism of onshore wind generation and green levies in general, which were seen to be adding to consumer pain (Carter and Clements, 2015). Flagship policies such as the

For the US, Saussay et al. (2022) find the share of low-carbon vacancies in total online job ads was fairly stable across the sample period of 2010–2019, averaging 1.35% during this time (see Figure 7.11, Appendix). This is at least three times greater than employment in high-carbon extraction jobs. There was a slight increase from 1.32% in 2010 to 1.44% in 2012, coinciding with the American Recovery and Investment Act (ARRA) green spending and its job creation effect, which was concentrated in manual occupations (Popp et al., 2021). The low-carbon job ad share then fell to below 1.3% in the middle sample years before increasing again from 2017 onwards. While the low-carbon job ad share for low-skill occupations (such as manual workers) increased from 0.97% to 1.12%, for high-skill occupations (such as managers and engineers) this share declined from 0.36% to 0.30%. The low-carbon job ad shares are higher for low-skill than for high-skill occupations, and this gap widened over the sample period.

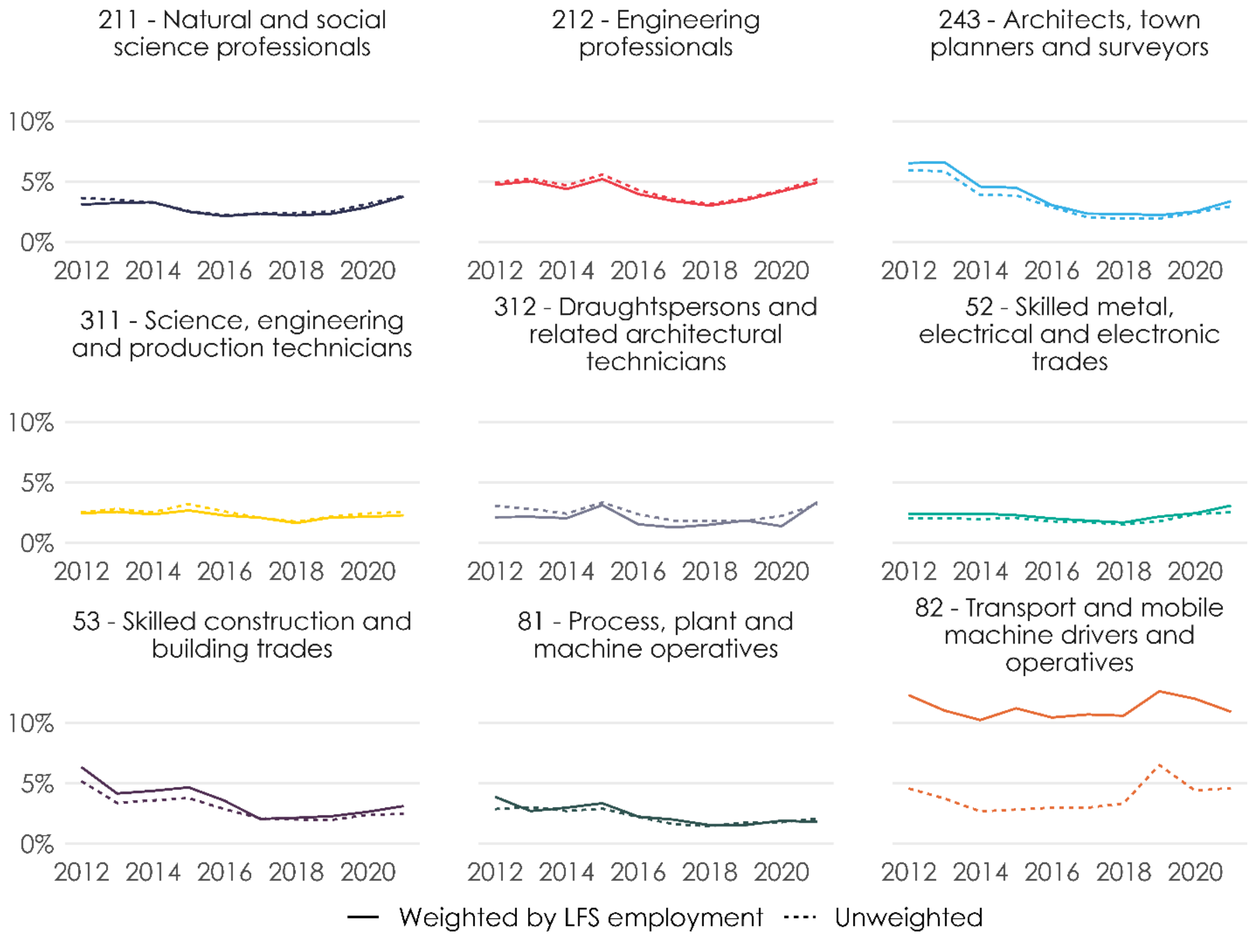
In both countries, the share of low-carbon jobs advertised is higher for low-skill occupations than for high-skill occupations. However, the gap is smaller in the UK than in the US and may even be narrowing – low-carbon job shares are rising faster for high- and middle-skill occupations than for low-skill. In the UK, it is customary and politically important to distinguish between middle- and low-skill occupations, both of which correspond to the low-skill group in the US (see Appendix, Table 7.1).

Occupation-specific trends

Turning now to the evolution of the demand for low-carbon jobs for the occupation categories with the highest low-carbon share (Figure 3 below), transport jobs (including public transport) have had the highest low-carbon ad share consistently throughout our UK sample. The share is higher in the UK, at around 11%, than in the US, at around 8%. In the UK, our occupations of interest all see a decrease or no statistically significant change in low-carbon share between the early sample years (2012–2015) and the later sample years (2019–2021) (see Table 7.5, Appendix). However, since the middle sample years (2016–2018), most of these occupations see a statistically significant increase that is particularly strong for architectural technicians, skilled metal and electronic trades, engineering professionals, and natural and social science professionals (Table 7.5). This is in contrast to the US, where the rising trend is limited to low-skill occupations (construction and extraction, installation and repair; see Figure 7.11, Appendix).

Green Homes Grant and the Heat and Buildings Strategy were largely considered a failure and were repealed. Subsidies from a number of demand- and supply-side renewable energy and energy efficiency programmes were also removed from 2013 onwards, as well as funding for home energy efficiency improvements, resulting in precipitous falls in the number of households insulating their lofts or cavity walls, by 92% and 74% in 2013 respectively, according to Evans (2022), numbers which have not recovered since. The application of a more stringent planning framework for new onshore wind power generation alongside the removal of subsidies through the Levy Control Framework (six years earlier than planned in 2015) for new development resulted in a steady drop in new production from 1.8GW in 2017, to 0.8GW in 2018 and 0.3GW in 2021. The Healthy Homes Standard, a series of regulations setting energy efficiency standards for new residential buildings, was shelved one year prior to its introduction and has resulted in around one million new-build homes being built with lower energy efficiency standards. The UK government's 2020 Ten Point Plan mobilised £12bn as part of the country's economic growth plan, with an aim of supporting 250,000 green jobs by 2030 with an interim target of 90,000 by 2025. The Ten Point Plan claims that UK low-carbon industries already support over 460,000 jobs. The Department for Business, Energy and Industrial Strategy (BEIS) claimed in May 2022 that 68,000 jobs had been "created and supported" or were "in the pipeline" (BEIS, 2022). However, reports indicate that BEIS does not have a definition of a green job, and many jobs included in the total figure belonged to disestablished schemes or are not slated for introduction until the end of this decade.

Figure 3. Evolution of low-carbon job ad share for selected SOC groups, 2012–2021, UK



Notes: Each sub-panel depicts the evolution of the share of low-carbon ads within each occupational group. The solid line represents the low-carbon share weighted by Labour Force Survey (LFS) employment (as described in the Figure 2 notes), while the dotted line represents the unweighted share calculated directly from the sample. Source: Authors.

4. The low-carbon skill gap

Previous studies from the US comparing skill requirements across different occupation categories have found that technical and, to a lesser extent, managerial skills are important for the adoption of green technologies (Vona et al., 2018). Saussay et al. (2022) improve on this previous work by taking advantage of the granularity offered by job vacancy data to compare skill requirements for green versus non-green jobs within the same occupation category, focusing on five broad skills families: cognitive, IT, management, social, and technical skills (see Table 7.6, Appendix). This US analysis finds that consistently across key occupations with a high share of low-carbon jobs, low-carbon vacancies are more likely than generic jobs to require skills in these five groups (see Figure 7.12).[3]

Low-carbon vacancies systematically require more skills

The UK results on the low-carbon skill gap are remarkably consistent with the US results. Figure 4 below illustrates the share of low-carbon, high-carbon and generic vacancies in the UK that contain at least one skill (extensive margin) or more than one skill (intensive margin) across each of our five skill families (see also Table 7.6, Appendix). Like the US, consistently across almost all our main occupation groups of interest in the UK low-carbon vacancies are more likely than generic jobs to require skills from all these skills families. This suggests that low-carbon jobs are systematically more skills-intensive than similar non-low-carbon jobs within the same occupation.

In both countries, the skill gap is found at both the extensive and intensive margins: in other words, low-carbon jobs are not only more likely to require these skills but they also require more of them compared with generic jobs. This gap in skill requirements for low-carbon versus generic jobs is particularly pronounced for technical and managerial skills, and to some extent social skills. Previous work based on cross-occupational comparisons in the US (Vona et al. 2018) and Europe (Marin and Vona, 2019) has similarly found a technical skill bias for low-carbon jobs. However, both the US and UK analyses indicate that for at least some occupations, low-carbon jobs tend to require more cognitive and IT skills compared with generic jobs, suggesting that the emerging skills gap resulting from the low-carbon transition is larger and broader than previously considered. This requirement for increased IT and cognitive skills for the low-carbon transition aligns with skill requirements for the ongoing digital transformation.

When comparing low-carbon skill gaps across Travel to Work Areas (TTWAs), these differences in skill requirements are statistically significant at conventional levels (see Table 7.7, Appendix). This is consistent with the US results.

Finding similar results in the US and UK suggests that we are uncovering something inherent about the skill profile of low-carbon jobs, and measuring the 'intrinsic' low-carbon skill gap. As a result, public investment to retrain workers to narrow the low-carbon skill gap would likely help to deliver a smooth, rapid and just transition.

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[3] Keywords to classify skills into these families are from Deming and Kahn (2018), except for the IT skills family, which is taken directly from the eponymous Lightcast skill family, and the technical skills family, which is based on Vona et al. (2018).

Differences across occupations

Important differences can be seen across occupational groups in the skill gaps in the UK, as was found in the US (see Table 7.7). In high-skill occupations, the technical and management skills gap is generally the most important one, both at the extensive and intensive margins, but significant gaps are generally found for all five skill families. However, for science professionals, cognitive and social skills gaps are also prominent. For draughtspersons, no significant gap is found at the extensive margin for cognitive or social skills. For architects, a negative gap is found for management skills, implying lower skill requirements for low-carbon vacancies. In the low-skill occupations in the UK, the skill gap between low-carbon and generic transport jobs is often negative, particularly at the extensive margin, while in the US, skill gaps between low-carbon and generic transport jobs are small or statistically insignificant, with the exception of social skills.

Figure 4. Comparison of broad skills requirements by occupation

Notes: Each panel represents the share of ads for a given occupation and category (generic, low-, or high-carbon) containing exactly one or two-plus skills pertaining to the broad skill family in the column header. Percentages refer to unweighted shares of ads obtained directly from the sample. Source: Authors.

Like low-carbon jobs, high-carbon job vacancies are systematically more skills-intensive in the US. In the UK this is true for high-skill Engineering professionals and Skilled construction trades, where skill profiles appear similar between high- and low-carbon jobs relative to generic jobs; if anything, low-carbon engineering jobs require fewer social and technical skills than high-carbon engineering jobs. However, this is not the case for machine operatives (see Table 7.6, Appendix), suggesting that in the UK displaced high-carbon workers in low-skill occupations will face a similar low-carbon skill gap to those in generic jobs.

The observed variation in skill gaps across occupations suggests that retraining solutions will need to be tailored to meet the specific needs of occupations affected by decarbonisation, or of the companies hiring these workers. Finding appropriate solutions to fill the skill gaps is likely to require cooperation among industry, trade unions, industry associations, technical and vocational colleges, and other social actors.

Similarly, the extent to which there is a skill shortage creating bottlenecks for the low-carbon transition is likely to be specific to sectors and occupations, as discussed in the next section under the wage gap results. Given that labour markets are local in area, skills shortages are also likely to be place-specific.

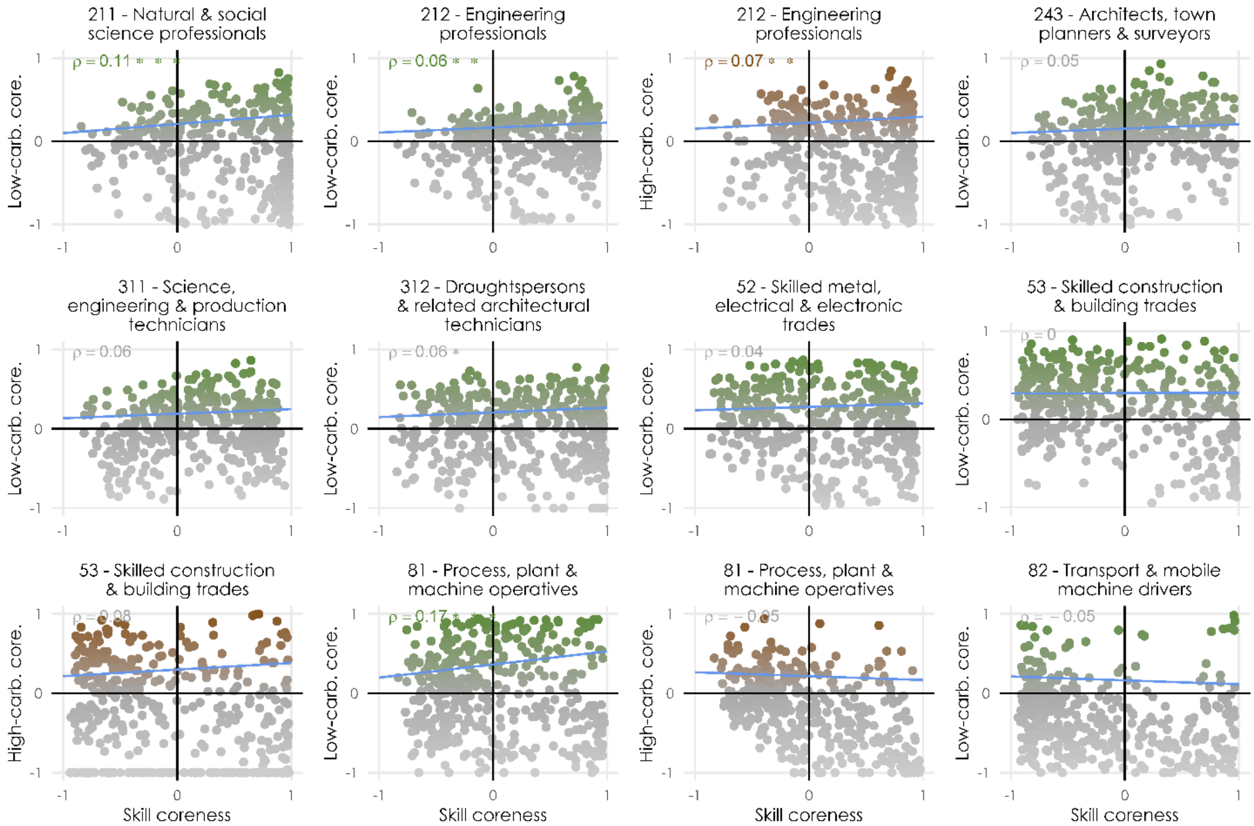
Specialisation versus diversification in reskilling paths

We use two measures of skill 'coreness' to explore variation in reskilling paths across occupational groups. First, the green skill coreness if high indicates that a skill is relatively more important in low-carbon ads than in other ads within a given occupation. Second, the generic skill coreness measures how important a skill is in a particular occupation relative to other occupations (see Saussay et al., 2022). Plotting the two indexes in Figure 5 below, we find a positive and significant correlation for natural and social scientists, engineering professionals, draughtspersons and related architectural technicians, and process, plant and machine operatives. These results are consistent with the US results (see Figure 7.13 in Appendix) and indicates that reskilling paths needed to shift towards green activities in these occupations require further specialisation.

Further, skills contained in both low-carbon and high-carbon engineering ads belong to the core set of skills for this occupation, implying that the switch to green is easy, requiring only incremental retraining. No specialisation–diversification patterns are found for other occupations such as construction workers, architects or transport workers. In the US, a negative correlation for business operation specialists (see Figure 7.13 in Appendix) suggests that here, moving into low-carbon likely involves diversifying the skill set by acquiring new technical, management or social skills that are beyond core curricula in business.

Overall, for most of the key occupations in the low-carbon transition, retraining is likely to require further specialisation, but 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 5. Specialisation versus 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 in the Appendix of Saussay et al. [2022] 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 ρ > 0 indicates specialisation: skills more prevalent in low- (resp. high-) carbon ads tend to be core skills of the occupation. Conversely, a significant ρ < 0 indicates diversification: skills important in low- (resp. high-) carbon ads are not part of the occupation's core skillset. ***p<0.01, **p<0.05, *p<0.1.*
Source: Authors

5. Where is the number of low-carbon jobs increasing?

One of the key challenges in delivering a 'just transition' and thereby maintaining crucial public support for net zero is to ensure that displaced workers in energy- or pollution-intensive industries find new jobs with similar pay and working conditions. The geographical dimension of the transition is important because high-carbon jobs are heavily spatially concentrated.

High-carbon jobs are spatially concentrated while low-carbon jobs show dispersal

High-carbon manual jobs in the fossil fuels sector are highly concentrated around centres of coal, crude oil, gas, and shale oil and gas extraction. In the UK these jobs are located close to the North Sea coast (see Figure 6). In the US these jobs are in areas including Wyoming, West Virginia, Oklahoma, Texas and the Appalachian region (Figure 7.14, Appendix). In contrast, in both the US and UK, advertised low-carbon jobs are spatially dispersed. This is true for both high- and low-skill occupations. The locational Gini coefficient for low-skilled jobs is twice as high for high-carbon ads as for low-carbon ads (0.68 versus 0.34 in the US and 0.46 versus 0.22 in the UK), indicating higher spatial concentration (see Table 7.9, Appendix). The spatial concentration of high-carbon jobs in the UK also holds for high-skill occupations. For example: 20% of all high-carbon engineering job ads are in Aberdeen, and roughly half of all high-carbon engineering jobs are in one of just three 'Travel to Work Areas' (TTWAs): London, Aberdeen or Glasgow. Insights from the literature on shocks caused by deindustrialisation (e.g. Autor et al., 2016, 2021) suggest that the spatial concentration of fossil fuel activities amplifies the negative effects of climate policies on fossil fuel communities.

In low-skill occupations, where concerns about displaced workers are focused, building and transport jobs are particularly spatially dispersed. In the UK, the areas with the highest shares of low-skill low-carbon job vacancies are located away from the South East of England. Although there is a high number of low-carbon vacancies of all skill levels in the Greater London area, low-carbon jobs are a relatively small share of the overall labour market compared with other areas. This suggests that the low-carbon transition can provide regionally-balanced economic opportunities in the UK.

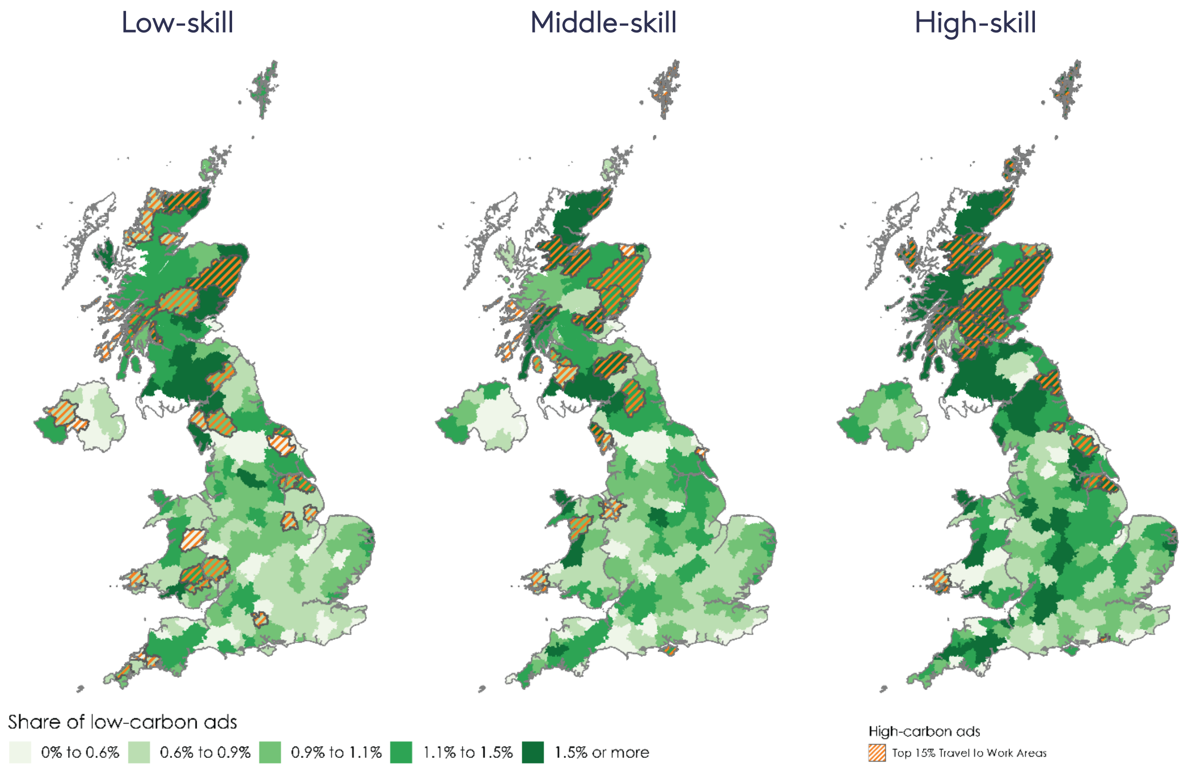
Varying geographical overlap between low- and high-carbon jobs

For low-skill occupations in both the US and the UK, we find limited geographical overlap between low- and high-carbon jobs. Appendix Table 7.8 shows that the correlation between shares of high- and low-carbon job ads across TTWAs is positive but statistically insignificant for low-skill occupations. This suggests that displaced low-skill workers may face limited new low-carbon employment opportunities locally. The magnitude of this problem is likely to be more severe in the US, where the share of workers in the fossil sectors are much higher than in the UK.[4]

In contrast, for middle- and high-skill jobs there is a significant geographical overlap between fossil-based high- and low-carbon jobs in the UK. Appendix Table 7.8 reports a statistically significant correlation between the shares of high- and low-carbon ads for middle-skill occupations and especially for high-skill occupations. Figure 4 below illustrates that several areas in Scotland in particular have a relatively high share of both high- and low-carbon job ads. There may be transferable skills, for example, between offshore oil and offshore wind workers.

[4] In the US, fossil fuel sector jobs accounted for 0.7% of total employment on average across commuting zones from 2000–2017 (Popp et al., 2021). In the UK in 2019 Q4, all Mining and Quarrying jobs accounted for 0.4% of total employment and in 2021 high-carbon job ads were just 0.13% of total vacancies (Eurostat, 2022).

Figure 6. Spatial distribution of low-carbon and high-carbon job ad shares by Travel to Work Area (TTWA) in the UK



Notes: From left to right, the maps depict in green shades the low-carbon job ad share (unweighted average across 2012-2021) for low-, middle- and high-skill jobs. TTWA regions approximate local labour market areas, defined by the ONS based on the criteria that at least 75% of working residents work in the area and at least 75% of people working in the area also live in the area. There are 228 TTWAs in the UK. The hashed orange overlay indicates the TTWAs with a high share (top 15%) of high-carbon job ads for that skill level. Source: Authors.

Implications for regional inequalities

So far, we have defined high-carbon jobs as fossil-fuel related jobs. However, in the UK, where hiring activity in fossil fuels is extremely small (and high-carbon job ads account for just 0.13% of vacancies in our sample in 2021), concerns about job destruction centre on jobs in energy-intensive industries, which have declined rapidly due to deindustrialisation since the 1970s. Remaining energy-intensive jobs have the potential to become low-carbon jobs if industrial sectors successfully manage the switch to carbon-neutral technologies including carbon capture, utilisation and storage (CCUS). Otherwise they are likely to decline, raising concerns about the reallocation cost for workers in these sectors. Widening the definition of high-carbon jobs to include energy-intensive industry sectors, we find tentative evidence that so far, the rise in low-carbon jobs is not occurring in these traditional industrial regions. This suggests that the potential for low-carbon jobs to fill the gap is not being fulfilled: we find no spatial overlap for any skill group between the low-carbon job ad share and job ad shares in energy-intensive sectors (see Table 7.10 and Figure 7.9, Appendix).

More positively, to the extent that low-carbon job creation is persistent, our data indicates that ambitious climate policies would not exacerbate existing regional inequalities in the UK. This is in contrast to the US, where low-skill high-carbon jobs tend to be concentrated in poorer areas while low-skill low-carbon jobs tend to be in wealthier areas (Saussay et al., 2022). In the UK, the low-carbon transition could reduce existing inequalities. The share of low-carbon ads tends to be higher in regions with higher unemployment, especially for middle-skill occupations, and regions with lower productivity, especially for low-skill occupations (see Tables 7.11 and 7.12, Appendix). Otherwise, spatial overlap between economically-disadvantaged areas and areas with a relatively high share of low-carbon job opportunities is limited.

6. Are low-carbon jobs better paid?

Low-carbon jobs are concentrated in occupations that pay higher wages

Previous studies have found a positive low-carbon wage premium when estimating the average differential in wages for green versus non-green jobs, across multiple years and a wide array of occupations (e.g. Vona et al., 2019; Valero et al., 2021). Our data suggests that in the UK, low-carbon jobs are concentrated in occupations that pay higher wages.[5] However, looking within narrowly-defined occupational groups reveals that in the UK and US, low-carbon jobs often are not paid any more than their non-low-carbon counterparts. For example, low-carbon finance jobs pay more than the average job or the average high-skill job, but may not pay more than the average finance job. This suggests that previous analyses that found a low-carbon wage premium may have to some extent been capturing this compositional feature of low-carbon jobs rather than a true premium for greenness.

Low-carbon wage premium has declined over time

The large sample size of job vacancy data enables us to uncover significant heterogeneity underlying this result, across both time and occupations. In the US, Saussay et al. (2022) find a positive and statistically significant low-carbon wage premium in the early years of the sample period (2010–2012) for all major occupation groups of interest (except for architects). The premium ranges from a large 16% for low-carbon transport jobs compared with similar non-low-carbon transport jobs, to a modest 2% differential in engineering (see Figure 7.15, Appendix). However, in the latter years of the sample period (2017–2019), a widespread and pronounced decline in the low-carbon wage premium occurred in the US. It disappeared for all but a couple of occupations: engineering and mapping technicians and installation, maintenance and repair jobs.

The UK results are consistent with the US findings. Figure 7 below shows wage regression results for our main occupation groups of interest in the UK analysis. Appendix Tables 7.14 and 7.15 show detailed results across specifications with different sets of covariates; the results are qualitatively similar to those depicted in the figure. In our early sample years (2012–2015) we find a positive and statistically significant low-carbon wage premium for jobs in engineering, skilled trades, and machine operatives, ranging from a 20% low-carbon premium for process, plant and machine operative jobs to a 6% wage differential for low-carbon engineering professionals compared with similar but non-green engineering jobs. The general positive wage premium during this earlier period could be indicative of several underlying drivers, including a skills shortage, policy pass-through or technological factors.

Similar to what we find in our US analysis, the premium declines over our sample period, even disappearing for several occupations. For example, we find that in late sample years (2018–2021) average salaries for low-carbon engineering jobs were not any different from average salaries for other similar engineering jobs. Jobs in skilled construction trades as well as process, plant and machine operatives maintained a low-carbon wage premium throughout our sample period, though it declined to 5% and 6% on average respectively by 2018–2021. The lack of a positive wage premium in the recent period despite low-carbon jobs having higher skill requirements is problematic for attracting workers to take up these jobs.

The average wage premium across all occupations declined over the sample period, becoming statistically insignificant by 2016 (Figure 7.10, Appendix). As discussed above, our occupation-level

[5] We run wage regressions on our full sample of job ads and years rather than separating by narrow occupation groups, and we similarly find a positive low-carbon wage premium on average across our sample (Table 7.16, Appendix). We also find a positive correlation between the average salary of an occupation and the share of low-carbon job ads observed for that occupation (Table 7.17). These correlations are not statistically significant except for middle-skill occupations, where the correlation is positive and statistically significant. Taken together with our wage regression analysis, this finding suggests that low-carbon jobs tend to be emerging in relatively well-paid occupations.

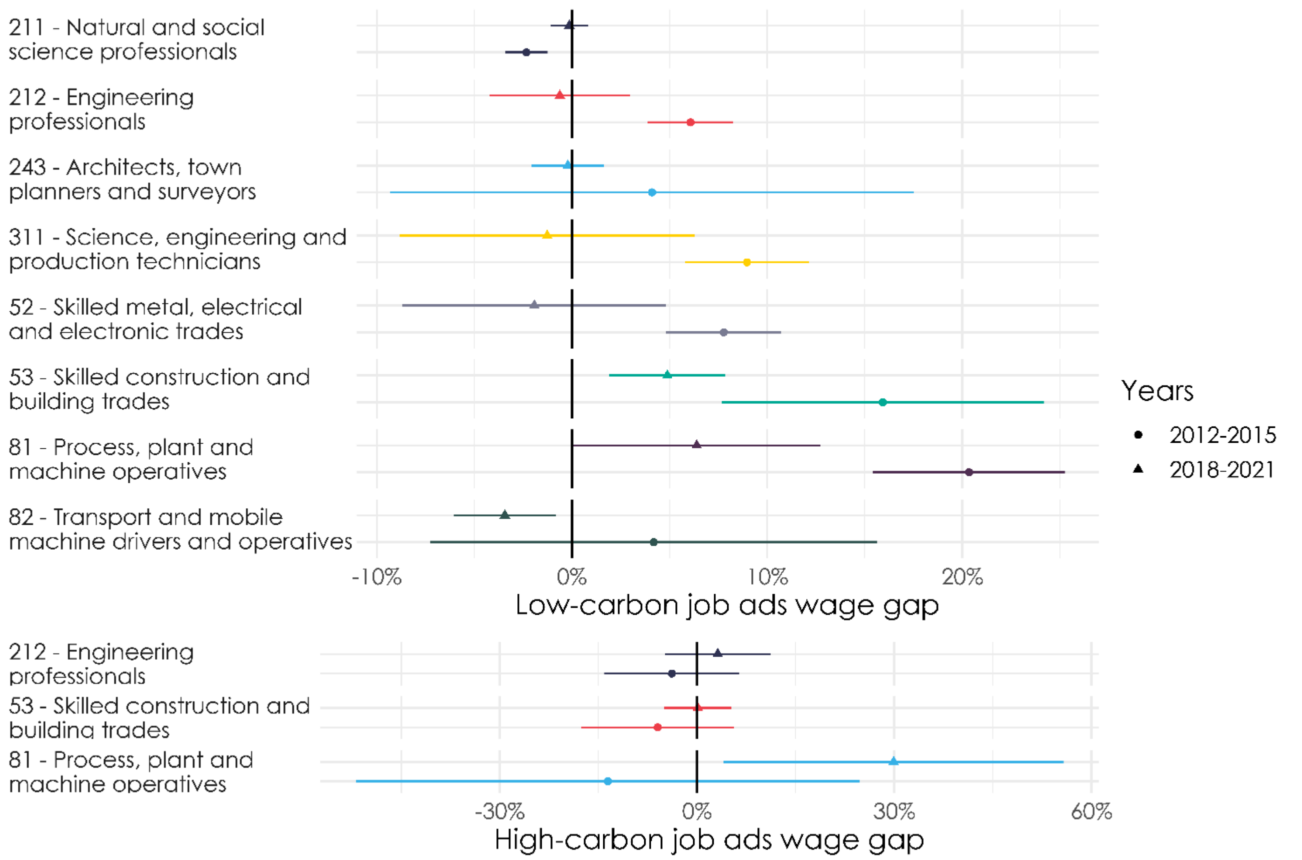
wage regressions demonstrate that although a low-carbon wage premium may exist for some occupations, many other occupations do not enjoy a premium.

Variations by occupation

The UK wage gap results are highly heterogeneous across our occupations. Compared with similar non-low-carbon jobs in the same occupation, we do not find any wage premium for low-carbon jobs in architecture and town planning, natural and social science, or transport. On the contrary, at times we observe a low-carbon wage penalty for professional jobs in natural and social science (2012–2015) and for transport jobs (2018–2021) compared with similar non-low-carbon jobs in the same occupation. In middle-/low-skilled occupations such as in construction and building, or process, plant and machine operatives, a positive low-carbon wage premium is found even in the more recent period.

Meanwhile, high-carbon jobs in the US command a large wage premium compared with non-high-carbon jobs in the same occupation, and this persists to the end of our sample period. Across 2017–2019, salaries for high-carbon engineering jobs were 8% higher on average compared with other engineering jobs; for high-carbon construction and extraction jobs the gap is 16%. In contrast, in the UK we do not find a wage premium for high-carbon jobs. The only exception to this result is for manual jobs in manufacturing (process, plant, and machine operatives), which see a statistically significant wage premium in latter sample years (2018–2021).

Figure 7. Low-carbon wage gap by occupation group: early vs. late sample years, UK



Notes: Regressions are weighted by Labour Force Survey employment and standard errors are clustered by 4-digit SOC code. Fixed effects included are year, Travel to Work Area (TTWA), 4-digit SOC code, 2-digit SIC code, and 5 bins for skill vector length: 1-2, 3-4, 5-6, 7-8, 9+.

7. Conclusion and implications for policymakers

Job ad data combined with methods developed in this research offer a powerful toolkit for understanding the changing demand for skills in the low-carbon transition and quantifying reallocation costs associated with reskilling.

The precise assessment of skill requirements of low-carbon activities will become even more important as massive labour reallocation towards low-carbon activities is expected under ambitious decarbonisation scenarios (Hafstead and Williams III, 2018; Castellanos and Heutel, 2019). Saussay et al. (2022) have developed a transparent and flexible approach to accurately isolate low-carbon jobs and quantify emerging skill and wage gaps using advertised job vacancy data, overcoming many of the issues with using sector- or occupation-based definitions. In this report we have applied this approach to characterise low-carbon jobs in the UK, drawing similar results to the US. This suggests that we are uncovering something inherent about the nature of low-carbon jobs, and we are measuring the 'intrinsic' low-carbon skill gap.

Policymakers can use this approach to monitor skill gaps associated with specific technologies and sectors that are relevant for the local economy, thus improving the effectiveness and the targeting of retraining programmes.

Low-carbon jobs are systematically more skill-intensive in most major occupations

A low-carbon skill gap exists across the US and UK, according to the detailed skill profiles in job postings – larger and broader than previously found using more aggregated analysis. The evidence that jobs in the low-carbon economy demand more skills from workers strengthens the case for public investment to help workers acquire skills, for example through targeted skills programmes. Our results on skill gaps thus support previous findings (Popp et al., 2021) that green fiscal push policies including stimulus packages require investments in retraining.

The magnitude and nature of the skill gap vary across occupational groups, suggesting that retraining solutions will need to be tailored to meet the specific needs of occupations affected by decarbonisation, or of the companies hiring these workers. Finding appropriate solutions to address the skill gap is likely to require cooperation among industry, trade unions, industry associations, technical and vocational schools, and other social actors.

Low-carbon jobs require higher skills but currently do not pay higher wages

This lack of a low-carbon wage premium is concerning for achieving the low-carbon transition. Low-carbon jobs are more likely to emerge in higher-paying occupations. This means that in aggregate, low-carbon jobs are better-paid. However, our detailed analysis reveals that when comparing low-carbon jobs with similar jobs within the same occupation, low-carbon jobs paid higher wages to compensate for higher skill requirements during the early 2010s in both the UK and US but this wage premium has largely disappeared in more recent years. In the UK, a small but positive low-carbon wage premium is still found in some middle-/low-skilled occupations such as in construction and building, and for process, plant and machine operatives.

The lack of a positive wage premium in recent years for low-carbon jobs despite their having higher skill requirements is problematic for attracting workers to take up these jobs. Reconciling the gap between higher skill requirements and a lack of wage premium is a neglected but important issue for managing the low-carbon transition.

Potentially high labour reallocation costs need to be factored into policy decisions and economic modelling

Evidence from the US and UK shows that the low-carbon transition entails potentially high labour reallocation costs associated with both the reskilling of workers to be more suited to low-carbon activities, and demands for regional labour mobility due to the location of low-carbon jobs.

Furthermore, the improved evidence base on reallocation costs should be used to calibrate integrated assessment and computational general equilibrium models used to assess macroeconomic impacts of climate change mitigation.

Policies are likely needed to support low-skill extraction workers who face limited alternative local employment

There is a limited skill gap between high-carbon fossil sector jobs and low-carbon jobs for high-skilled workers in both the US and UK, and for low-skill workers in the US, suggesting a limited need for reskilling. In contrast, for low-skill jobs in extraction in the UK, skill requirements are not particularly high, suggesting these workers will require skills training if moving into a low-carbon job. In the US, high-carbon low-skilled jobs command a significant wage premium compared with similar jobs in the same occupation, including low-carbon jobs. In these circumstances, solutions other than reskilling, for example targeted place-based policies, may be more effective in preventing workers in these communities being left behind in the low-carbon transition.

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Appendix of additional tables and figures

Additional tables and figures for UK analysis

Table 7.1: Main occupation groups of interest, US versus UK analysis

US Occupation groups	UK Occupation groups
High skill	**High skill**
19-2 - Physical scientists	211 - Natural and social science professionals
17-2 - Engineers	212 - Engineering professionals
17-1 - Architects, surveyors, and cartographers	243 - Architects, town planners and surveyors
17-3 - Engineering and mapping technicians	311 - Science, engineering and production technicians
	312 - Draughtspersons and related architectural technicians
13-1 - Business operations specialists	
Low skill	**Middle skill**
49 - Installation, maintenance, and repair	52 - Skilled metal, electrical and electronic trades
47 - Construction and extraction	53 - Skilled construction and building trades
	Low skill
	81 - Process, plant and machine operatives
53 - Tranportation and material moving	82 - Transport and mobile machine drivers and operatives

Notes: This table lists the occupations of focus in this report, with both classification codes and corresponding names for both the US and UK analyses. The US analysis uses the US 2010 Standard Occupation Classification (SOC) system. The UK analysis uses the UK 2010 Standard Occupation Classification system. We follow previous literature by splitting the UK occupations into 3 categories (high, middle, and low); the US "Low-skill" category corresponds to both the middle- and low-skill categories in the UK classification.

Table 7.2: Representativeness of Lightcast ads dataset vs. UK Labour Force Survey (LFS) employment

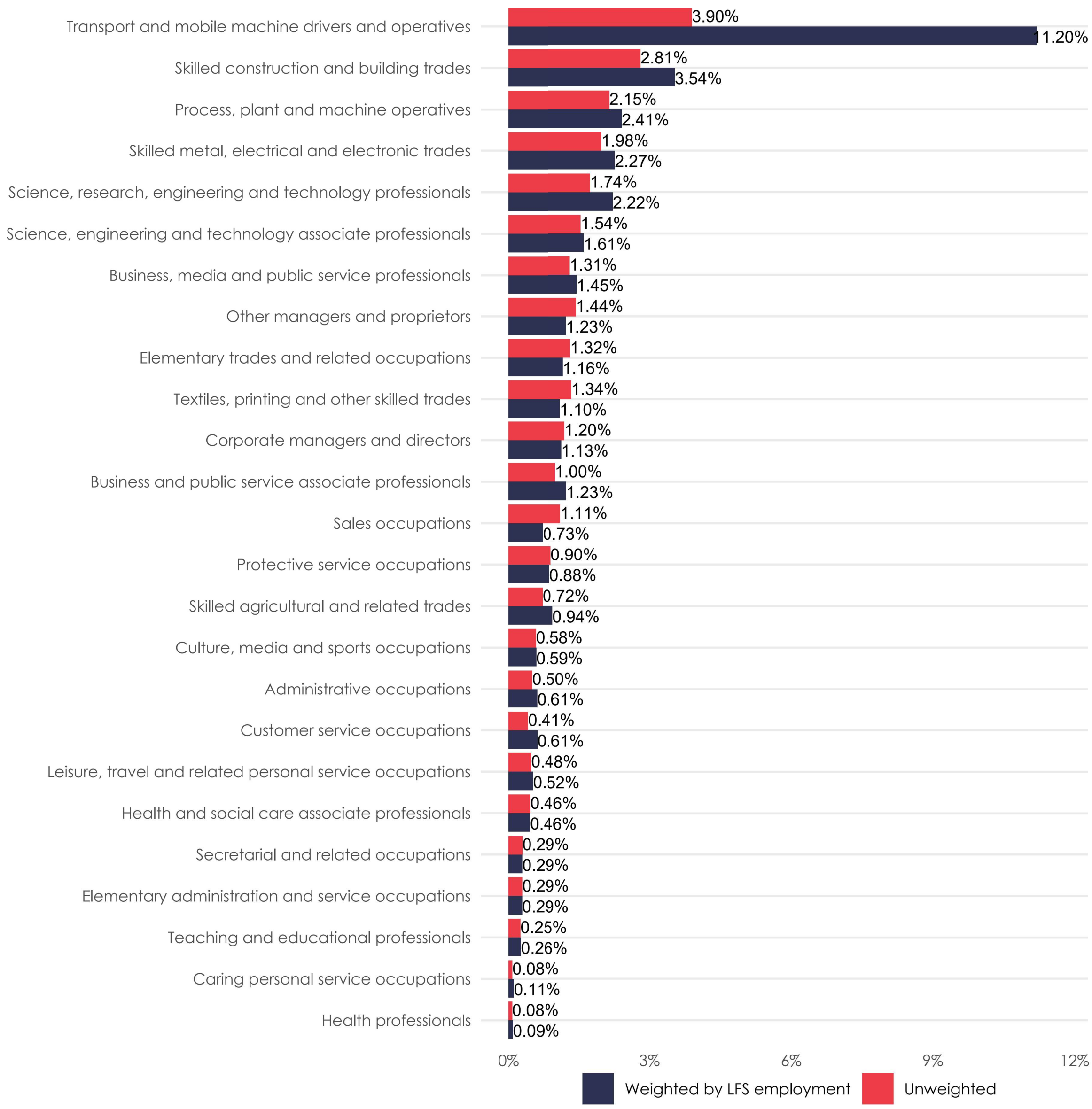
UK SOC sub-major group	Ad count	Unweighted ad share	LFS employment share
11 - Corporate managers and directors	5,057,687	7.5%	7.5%
12 - Other managers and proprietors	2,387,459	3.6%	3.1%
21 - Science, research, engineering and technology professionals	9,995,807	14.9%	5.8%
22 - Health professionals	3,698,040	5.5%	4.4%
23 - Teaching and educational professionals	3,206,058	4.8%	5.0%
24 - Business, media and public service professionals	6,648,119	9.9%	5.7%
31 - Science, engineering and technology associate professionals	3,519,232	5.2%	1.9%
32 - Health and social care associate professionals	809,357	1.2%	1.5%
33 - Protective service occupations	146,408	0.2%	1.2%
34 - Culture, media and sports occupations	1,070,923	1.6%	2.4%
35 - Business and public service associate professionals	6,126,847	9.1%	7.5%
41 - Administrative occupations	4,579,609	6.8%	8.2%
42 - Secretarial and related occupations	1,278,852	1.9%	2.2%
51 - Skilled agricultural and related trades	70,803	0.1%	1.1%
52 - Skilled metal, electrical and electronic trades	1,754,014	2.6%	3.6%
53 - Skilled construction and building trades	609,895	0.9%	3.4%
54 - Textiles, printing and other skilled trades	1,487,929	2.2%	2.1%
61 - Caring personal service occupations	3,203,067	4.8%	7.2%
62 - Leisure, travel and related personal service occupations	650,721	1.0%	2.0%
71 - Sales occupations	4,596,806	6.8%	5.6%
72 - Customer service occupations	1,803,337	2.7%	1.9%
81 - Process, plant and machine operatives	653,495	1.0%	2.6%
82 - Transport and mobile machine drivers and operatives	1,037,766	1.5%	3.6%
91 - Elementary trades and related occupations	331,210	0.5%	1.7%
92 - Elementary administration and service occupations	2,433,032	3.6%	8.8%

Table 7.3: Summary statistics by 1-digit SOC code

	Ad Count	Skills count		Salary		
		Mean	St. Dev	Share missing	Mean	St. Dev
All job ads						
Generic	68,207,341	5.7	5.0	0.38	35,691	21,176
High carbon	22,273	6.1	5.3	0.53	41,520	24,017
Low carbon	739,680	8.2	6.2	0.42	39,817	19,951
Managers, directors and senior officials						
Generic	7,350,091	6.6	5.3	0.37	44,637	22,386
Low carbon	94,988	9.6	6.4	0.43	49,270	21,259
Professional occupations						
Generic	23,263,273	6.4	5.6	0.37	45,291	22,978
High carbon	13,550	7.7	5.6	0.61	50,067	25,000
Low carbon	271,687	9.4	6.3	0.44	44,642	20,172
Associate professional and technical occupations						
Generic	11,546,060	6.3	5.3	0.36	34,112	18,648
Low carbon	126,303	8.2	6.0	0.42	38,115	18,872
Administrative and secretarial occupations						
Generic	5,831,646	5.8	4.3	0.34	24,379	13,124
Low carbon	26,749	9.1	6.4	0.43	30,633	17,534
Skilled trades occupations						
Generic	3,847,790	3.5	3.3	0.35	28,107	12,194
High carbon	2,308	3.2	3.2	0.31	34,184	9,753
Low carbon	71,954	6.4	5.1	0.39	33,693	14,454
Caring, leisure and other service occupations						
Generic	3,848,078	3.3	2.7	0.35	20,952	10,066
Low carbon	5,702	7.7	5.6	0.42	27,188	16,874
Sales and customer service occupations						
Generic	6,341,638	5.5	4.3	0.37	26,955	15,447
Low carbon	58,374	6.8	5.1	0.38	36,761	19,042
Process, plant and machine operatives						
Generic	1,607,376	2.9	3.0	0.31	26,027	11,751
High carbon	29,335	3.3	2.8	0.27	20,705	9,095
Low carbon	54,159	3.4	3.4	0.36	26,904	12,585
Elementary occupations						
Generic	2,752,708	3.4	3.0	0.40	20,282	10,165
Low carbon	11,411	6.0	5.2	0.41	24,878	13,727
Missing SOC code						
Generic	1,795,761	5.7	4.9	0.77	38,443	24,172
Low carbon	18,141	8.1	5.9	0.77	38,456	21,302

Notes: This table shows the (unweighted) number of ads for each 1-digit SOC code by category (Generic, High-carbon, and Low-carbon), as well as summary statistics for the number of skills required and salary across ads in each occupation-category. "St. Dev" refers to standard deviation and "Share missing" refers to the share of observations that are missing.

Figure 7.7: Low-carbon ad share by 2-digit SOC code, 2012-2021



Notes: The table presents the low-carbon ad share for each 2-digit SOC code. "Unweighted" values indicate the share of low-carbon ads computed directly from the Lightcast data; "Weighted by LFS employment" values are computed taking the weighted average of low-carbon ad share across 4-digit SOC codes, using ONS Labour Force Survey (LFS) 4-digit SOC employment counts as weights. Occupations are ordered by the weighted low-carbon ad share.

Table 7.4: Evolution of the share of low-carbon ads by Travel to Work Area (TTWA): Early (2012-15) versus middle (2016-2018) and late (2019-2021) sample periods

	All	Low skill	Middle skill	High skill
2016-18 vs. 2012-15	-0.004***	-0.003***	-0.007***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.000)
2019-21 vs. 2012-15	-0.001	-0.001	-0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.016***	0.019***	0.017***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
2019-21 vs. 2016-18	0.0031***	0.0024***	0.0026***	0.0041***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Observations	672	672	672	672
R2	0.173	0.034	0.233	0.206

Notes: For each sample period, we obtain the mean share of low-carbon job ads within each TTWA and skill category. We regress this low-carbon ad share on a categorical variable indicating the sample period, using early sample years (2012-2015) as the reference category. Regressions are weighted by the count of ads by TTWA (weighted by LFS employment by 4-digit SOC) and standard errors are clustered by TTWA. "2019-21 vs. 2016-18" shows the results of a t-test of the equality of the coefficients on the middle and late sample periods. High-skill occupations are those in UK SOC Major groups 1, 2, and 3; middle-skill occupations are in SOC Major groups 4 and 5; low-skill occupations are in SOC Major Groups 6 and above. ***p<0.01, **p<0.05, *p<0.1.

Table 7.5: Evolution of the share of low-carbon ads by Travel to Work Area (TTWA) in selected SOC groups: Early (2012-15) versus middle (2016-2018) and late (2019-2021) sample periods

	211	212	243	311	312	53	52	81	82
2016-18 vs. 2012-15	-0.009***	-0.015***	-0.032***	-0.005***	-0.009**	-0.022***	-0.006***	-0.014***	-0.008
	(0.002)	(0.002)	(0.007)	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)	(0.007)
2019-21 vs. 2012-15	-0.001	-0.006**	-0.029***	-0.003***	-0.001	-0.022***	0.002	-0.016***	0.003
	(0.002)	(0.003)	(0.007)	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)	(0.007)
Constant	0.035***	0.050***	0.059***	0.026***	0.031***	0.051***	0.024***	0.035***	0.117***
	(0.003)	(0.003)	(0.008)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)	(0.006)
2019-21 vs. 2016-18	0.0085***	0.0083***	0.0024**	0.0018*	0.0080*	-0.0001	0.0079***	-0.0022	0.0105**
	(0.0018)	(0.0012)	(0.0010)	(0.0010)	(0.0045)	(0.0011)	(0.0012)	(0.0014)	(0.0045)
Observations	422	610	539	606	344	559	596	521	613
R2	0.018	0.094	0.218	0.016	0.009	0.194	0.057	0.071	0.005

Notes: For each sample period, we obtain the mean share of low-carbon job ads within each TTWA and occupation group. We regress this low-carbon ad share on a categorical variable indicating the sample period, using early sample years (2012-2015) as the reference category. Regressions are weighted by the count of ads by TTWA (weighted by LFS employment by 4-digit SOC) and standard errors are clustered by TTWA. "2019-21 vs. 2016-18" shows the results of a t-test of the equality of the coefficients on the middle and late sample periods. High-skill occupations are those in UK SOC Major groups 1, 2, and 3; middle-skill occupations are in SOC Major groups 4 and 5; low-skill occupations are in SOC Major Groups 6 and above. Occupation groups are labelled by SOC codes in the column headers: 211 - Natural And Social Science Professionals, 212 - Engineering Professionals, 243 - Architects, Town Planners And Surveyors, 311 - Science, Engineering And Production Technicians, 312 - Draughtspersons And Related Architectural Technicians, 52 - Skilled Metal, Electrical And Electronic Trades, 53 - Skilled Construction And Building Trades, 81 - Process, Plant And Machine Operatives, and 82 - Transport And Mobile Machine Drivers And Operatives. ***p<0.01, **p<0.05, *p<0.1.

Table 7.6: Broad skills requirements by occupation

	Cognitive		IT		Management		Social		Technical	
	1	2+	1	2+	1	2+	1	2+	1	2+
211 - Natural and social science professionals										
Generic	33.9%	11.0%	8.6%	5.9%	17.4%	7.6%	24.0%	11.1%	9.1%	1.8%
Low carbon	42.9%	14.0%	12.5%	8.2%	23.4%	14.0%	31.3%	15.8%	13.6%	4.7%
212 - Engineering professionals										
Generic	12.6%	2.1%	12.8%	13.3%	19.6%	8.9%	21.0%	7.4%	24.6%	14.9%
High carbon	14.1%	1.7%	15.8%	9.8%	26.4%	15.0%	25.1%	13.1%	26.5%	23.3%
Low carbon	14.2%	2.7%	16.1%	10.2%	24.2%	14.3%	23.6%	9.6%	26.1%	21.0%
243 - Architects, town planners and surveyors										
Generic	7.1%	0.8%	9.5%	8.8%	28.2%	16.0%	23.8%	8.2%	18.5%	5.1%
Low carbon	8.9%	1.0%	10.9%	8.1%	26.1%	21.1%	24.8%	9.4%	23.1%	12.6%
311 - Science, engineering and production technicians										
Generic	12.5%	2.1%	9.7%	8.4%	15.7%	5.6%	21.9%	6.6%	16.4%	4.7%
Low carbon	15.6%	2.2%	12.5%	9.8%	18.8%	9.6%	24.3%	8.1%	20.8%	7.9%
312 - Draughtspersons and related architectural technicians										
Generic	8.6%	1.2%	11.6%	6.1%	15.3%	6.2%	21.4%	7.1%	21.3%	9.0%
Low carbon	9.0%	0.9%	14.4%	6.8%	20.7%	10.7%	20.4%	9.0%	26.6%	15.1%
52 - Skilled metal, electrical and electronic trades										
Generic	6.8%	0.5%	6.0%	6.6%	8.3%	2.5%	18.1%	4.9%	17.8%	3.6%
Low carbon	9.5%	0.9%	8.8%	5.6%	13.4%	5.0%	20.2%	5.7%	19.1%	6.7%
53 - Skilled construction and building trades										
Generic	2.9%	0.2%	2.5%	1.0%	8.2%	2.3%	10.6%	2.1%	7.4%	1.0%
High carbon	3.7%	0.0%	5.2%	1.8%	5.7%	4.6%	14.8%	4.2%	7.8%	1.5%
Low carbon	5.8%	0.4%	5.2%	2.1%	12.3%	4.4%	15.7%	2.8%	11.8%	3.8%
81 - Process, plant and machine operatives										
Generic	6.6%	0.7%	6.1%	5.7%	11.9%	4.3%	17.5%	5.0%	14.6%	2.4%
High carbon	4.5%	0.2%	3.6%	2.2%	9.2%	3.0%	15.2%	3.5%	15.0%	2.2%
Low carbon	9.5%	1.2%	8.4%	6.6%	17.3%	8.6%	21.0%	5.5%	19.6%	5.0%
82 - Transport and mobile machine drivers and operatives										
Generic	2.0%	0.1%	14.8%	1.2%	4.8%	1.1%	18.6%	2.8%	2.2%	0.1%
Low carbon	1.4%	0.2%	3.7%	1.1%	4.0%	1.3%	9.1%	2.1%	1.5%	0.2%

Notes: Each values represents the share of ads for a given occupation and category (generic, low-, or high-carbon) containing *exactly one* (1) or *two or more* (2+) skills pertaining to the broad skill family in the column header. Percentages reported are unweighted shares of ads obtained directly from the sample.

Table 7.7: Skill gap magnitude across TTWAs

(a) Extensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
211 - Natural And Social Science Professionals	11.10% ***	3.80% ***	5.30% ***	7.20% ***	5.00% ***
212 - Engineering Professionals	1.50% ***	3.60% ***	4.90% ***	2.50% ***	1.50% *
243 - Architects, Town Planners And Surveyors	1.80% ***	1.30% **	-1.80% **	1.40% **	4.60% ***
311 - Science, Engineering And Production Technicians	3.60% ***	3.20% ***	3.60% ***	2.90% ***	4.50% ***
312 - Draughtspersons And Related Architectural Technicians	1.90%	4.40% ***	7.40% ***	0.00%	5.80% ***
52 - Skilled Metal, Electrical And Electronic Trades	3.10% ***	3.00% ***	5.70% ***	2.30% ***	1.00% **
53 - Skilled Construction And Building Trades	3.30% ***	3.30% ***	5.10% ***	5.90% ***	4.40% ***
81 - Process, Plant And Machine Operatives	3.80% ***	3.50% ***	6.20% ***	4.00% ***	5.10% ***
82 - Transport And Mobile Machine Drivers And Operatives	-0.20%	-11.30% ***	-0.60% *	-9.60% ***	-0.30% **
b) High carbon vs Generic ads					
212 - Engineering Professionals	2.70% ***	3.70% ***	7.10% ***	4.70% ***	2.20% **
53 - Skilled Construction And Building Trades	3.70% ***	7.90% ***	1.00%	6.60% ***	4.50% ***
81 - Process, Plant And Machine Operatives	-1.80% ***	-2.10% ***	-2.40% ***	-2.00% **	1.00%
c) Low carbon vs High carbon ads					
212 - Engineering Professionals	-1.20%	-0.20%	-2.20%	-2.20%	-0.70%
53 - Skilled Construction And Building Trades	-0.40%	-4.60% ***	4.00% **	-0.70%	-0.10%
81 - Process, Plant And Machine Operatives	5.60% ***	5.60% ***	8.60% ***	6.00% ***	4.20% ***

(b) Intensive margin

SOC group	Cognitive	IT	Management	Social	Technical
a) Low carbon vs Generic ads					
211 - Natural And Social Science Professionals	3.30% ***	2.80% ***	7.20% ***	5.20% ***	3.20% ***
212 - Engineering Professionals	0.60% **	-3.20% ***	5.70% ***	2.40% ***	6.50% ***
243 - Architects, Town Planners And Surveyors	0.50% ***	-0.70%	5.20% ***	1.30% ***	7.50% ***
311 - Science, Engineering And Production Technicians	0.60% *	2.00% ***	4.50% ***	1.80% ***	3.50% ***
312 - Draughtspersons And Related Architectural Technicians	0.50%	2.10% **	6.60% ***	3.80% ***	8.00% ***
52 - Skilled Metal, Electrical And Electronic Trades	0.90% ***	-0.60%	2.90% ***	1.30% ***	3.50% ***
53 - Skilled Construction And Building Trades	0.90% ***	2.20% ***	2.90% ***	1.40% ***	3.40% ***
81 - Process, Plant And Machine Operatives	1.30% ***	2.60% ***	5.50% ***	1.60% ***	3.90% ***
82 - Transport And Mobile Machine Drivers And Operatives	0.20% ***	0.20%	0.50% ***	-0.40% **	0.30% ***
b) High carbon vs Generic ads					
212 - Engineering Professionals	0.10%	-2.90% **	6.80% ***	6.90% ***	9.70% ***
53 - Skilled Construction And Building Trades	–	3.30% ***	7.40% ***	6.80% ***	3.60% **
81 - Process, Plant And Machine Operatives	0.10%	-2.90% ***	-0.90% ***	-1.40% ***	0.20%
c) Low carbon vs High carbon ads					
212 - Engineering Professionals	0.50%	-0.30%	-1.10%	-4.50% ***	-3.20% *
53 - Skilled Construction And Building Trades	–	-1.00%	-4.50%	-5.40% ***	-0.30%
81 - Process, Plant And Machine Operatives	1.20% ***	5.50% ***	6.40% ***	2.90% ***	3.60% ***

Notes: For each Travel to Work Area (TTWA), we calculate the share of ads for a given occupation and category (generic, low-, or high-carbon containing *exactly one* (extensive margin) or *two or more* (intensive margin) skills in each of the five broad skill families. We then use the resulting distribution to test the statistical significance of the skill gap magnitude between each ad-category pair. Table cells without an estimate (shown by "–") indicate insufficient observations of the skill family within the occupation to test the statistical significance of the skill gap. ***p<0.01, **p<0.05, *p<0.1.

Table 7.8: Correlation between the share of low- and high-carbon ads by Travel to Work Areas (TTWAs)

	Unweighted	Weighted by ad count	Weighted by population > 16
Low skill			
$\log(1 + s_{hc,ttwa})$	0.061	0.496	0.784
	(0.436)	(1.711)	(1.146)
Observations	223	223	213
R2	0.000	0.001	0.004
Middle skill			
$\log(1 + s_{hc,ttwa})$	1.301	1.096**	1.047*
	(1.748)	(0.489)	(0.603)
Observations	221	221	211
R2	0.011	0.015	0.012
High skill			
$\log(1 + s_{hc,ttwa})$	1.466***	1.040***	1.316***
	(0.388)	(0.384)	(0.488)
Observations	222	222	212
R2	0.059	0.052	0.060

Notes: This table presents estimates of $\beta_{lc,hc}$ in the regression model $log(1 + s_{lc,ttwa}) = \beta_{lc,hc} log(1 + s_{hc,ttwa}) + \varepsilon_{ttwa}$. $s_{lc,ttwa}$ is the low-carbon share of job ads from 2012-2021 for a given TTWA, and $s_{hc,ttwa}$ is the corresponding share for high-carbon job ads. Column (1) presents unweighted regression results, column (2) shows results weighted by the number of job ads between 2012 and 2021 in each TTWA, and column (3) shows results weighted by average population in each TTWA between 2012 and 2021. The top panel shows results for low-skill occupations (UK SOC Major groups 6 and above), the middle panel shows results for middle-skill occupations (UK SOC Major groups 4 and 5), and the bottom panel is results for high-skill occupations (UK SOC Major groups 1, 2, and 3). Standard errors are robust. ***p<0.01, **p<0.05, *p<0.1.

Table 7.9: Locational Gini

	Low carbon ads	High carbon ads		Generic ads
Low skill	0.22	0.46	Construction operatives	0.16
Middle skill	0.26	0.67	Skilled construction tradespersons	0.17
High skill	0.28	0.76	Engineers	0.23

Notes: This table presents the Locational Gini for the share of low-carbon jobs ads by TTWA, the share of high-carbon job ads by TTWA, and the share of generic ads in each of the three occupation groups listed: Construction operatives (SOC minor groups 814 and 912), Skilled construction and building trades (SOC sub-major group 53), and Engineering professionals (SOC minor group 212). Each of the Gini Coefficients presented above, indexed by k, is calculated as:

$$LocGini_k = \Delta/4u$$

where

$$\Delta = \{1/[n(n-1)]\} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|$$

i, j = Travel to Work Areas ($i \neq j$)

n = Total number of TTWAs

u = mean of the share variable k across all TTWA

$x_{i(j)}$ = (1) [TTWA i's(j's) share of low-carbon low-skill ads] / [TTWA i's (j's) share of all low-skill ads]

= (2) [TTWA i's(j's) share of high-carbon low-skill ads] / [TTWA i's (j's) share of all low-skill ads]

= (3) [TTWA i's(j's) share of SOC 814 & 912 ads] / [TTWA i's (j's) share of all low-skill ads]

= (4) [TTWA i's(j's) share of low-carbon middle-skill ads] / [TTWA i's (j's) share of all middle-skill ads]

= (5) [TTWA i's(j's) share of high-carbon middle-skill ads] / [TTWA i's (j's) share of all middle-skill ads]

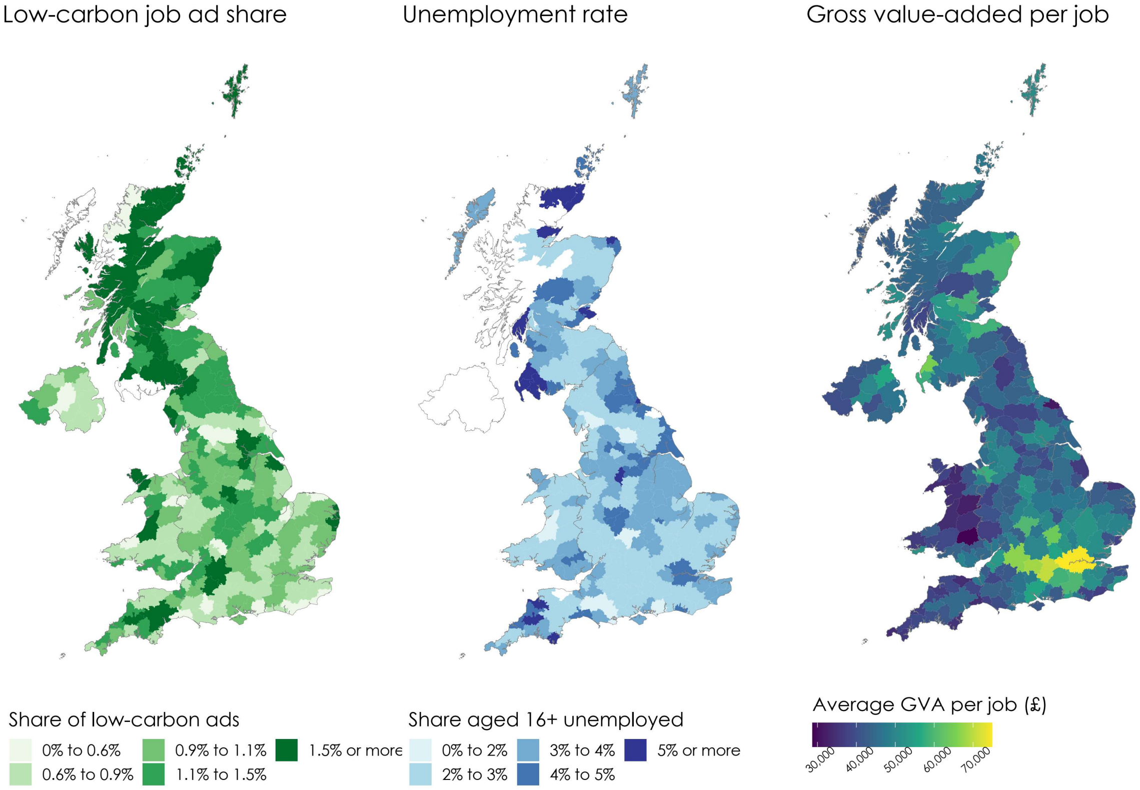
= (6) [TTWA i's(j's) share of SOC 53 ads] / [TTWA i's (j's) share of all middle-skill ads]

= (7) [TTWA i's(j's) share of low-carbon high-skill ads] / [TTWA i's (j's) share of all high-skill ads]

= (8) [TTWA i's(j's) share of high-carbon high-skill ads] / [TTWA i's (j's) share of all high-skill ads]

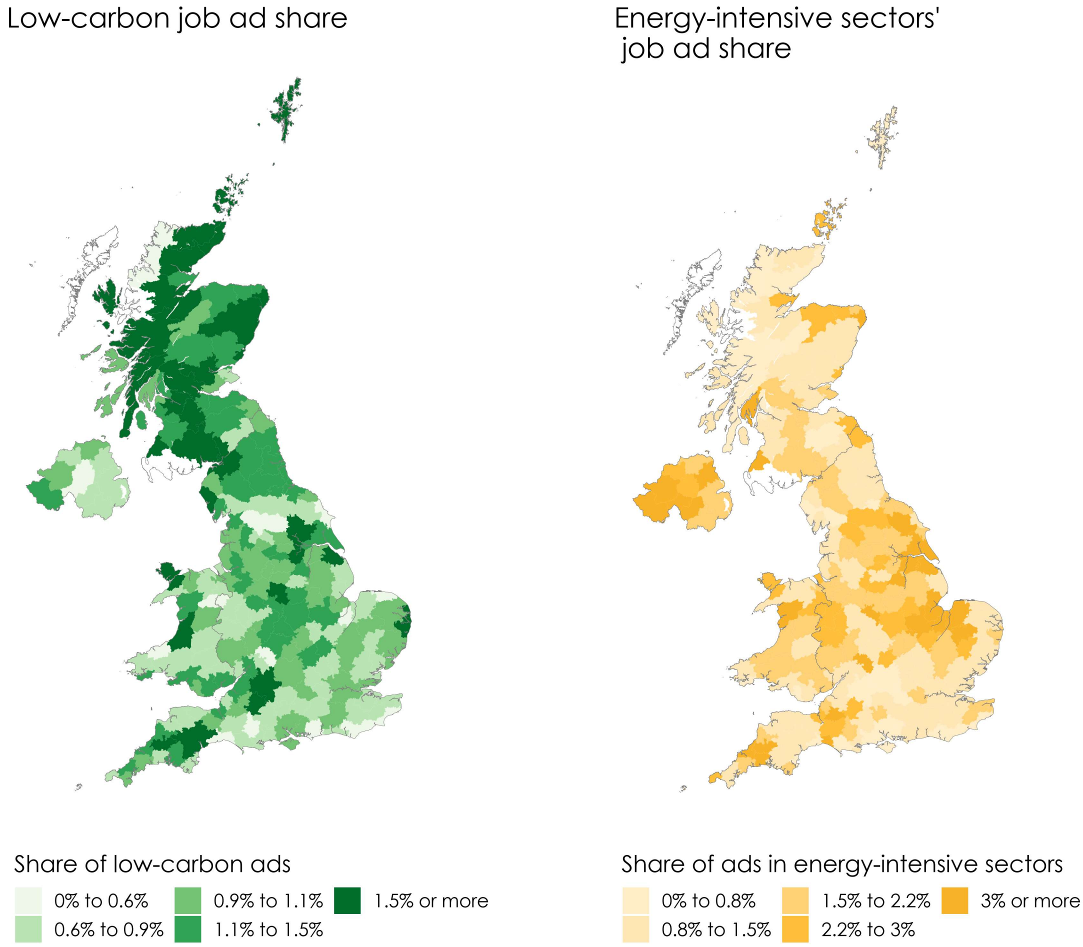
= (9) [TTWA i's(j's) share of SOC 212 ads] / [TTWA i's (j's) share of all high-skill ads]

Figure 7.8: Spatial distribution of low-carbon share of job ads, unemployment rate, and labour productivity by UK Travel to Work Area (TTWA)



Notes: The left panel illustrates the low-carbon share of job ads for all skill levels (unweighted average across 2012-2021) by TTWA. The middle panel is the average share of people aged 16+ that are unemployed in each TTWA from 2012-2021 (data from the ONS Labour Force Survey). The rightmost panel depicts labour productivity, measured by average gross value added per job in each TTWA between 2012 and 2021 (data from the ONS).

Figure 7.9: Low-carbon ad share and energy-intensive sector job ad shares by TTWA



Notes: The left panel shows the low-carbon share of job ads for all skill levels (unweighted average across 2012-2021) by TTWA. The right panel depicts the share of job ads (unweighted average across 2012-2021) in the most energy-intensive industrial sectors in the UK: basic metals (SIC code 24); chemicals (SIC 20); oil refining (SIC 19.2); food and drink (SIC 10 and 11); pulp and paper (SIC 17); cement (SIC 23.5 and 23.6); glass (SIC 23.1); ceramics (SIC 23.3 and 23.4). The count of energy-intensive sector vacancies discludes the small number of jobs in these sectors that are low-carbon job ads.

Table 7.10: Correlation between the share of low-carbon ads and the share of ads in energy-intensive sectors by Travel to Work Areas (TTWAs)

	Unweighted	Weighted by ad count	Weighted by population > 16
Low skill			
log($s_{ei,ttwa}$)	-0.044***	0.025	0.053
	(0.014)	(0.050)	(0.061)
Observations	223	223	213
R2	0.018	0.002	0.005
Middle skill			
log($s_{ei,ttwa}$)	-0.014	-0.027*	-0.010
	(0.032)	(0.016)	(0.016)
Observations	217	217	207
R2	0.002	0.012	0.002
High skill			
log($s_{ei,ttwa}$)	0.022	0.025	0.025
	(0.033)	(0.026)	(0.020)
Observations	222	222	212
R2	0.007	0.006	0.006

Notes: This table presents estimates of $\beta_{lc,ei_{ttwa}}$ in the regression model $log(1 + s_{lc,ttwa}) = \beta_{lc,ei_{ttwa}} log(1 + s_{ei,ttwa}) + \varepsilon_{ttwa}$. $s_{lc,ttwa}$ is the low-carbon share of job ads from 2012-2021 for a given TTWA, and $s_{ei,ttwa}$ is average share of (non-low-carbon) job ads in energy-intensive sectors between 2012 and 2021 for a given TTWA. Column (1) presents unweighted regression results, column (2) shows results weighted by the number of job ads between 2012 and 2021 in each TTWA, and column (3) shows results weighted by average population in each TTWA between 2012 and 2021. The top panel shows results for low-skill occupations (UK SOC Major groups 6 and above), the middle panel shows results for middle-skill occupations (UK SOC Major groups 4 and 5), and the bottom panel is results for high-skill occupations (UK SOC Major groups 1, 2, and 3). Standard errors are robust. ***p<0.01, **p<0.05, *p<0.1.

Table 7.11: Correlation between the share of low-carbon ads and unemployment rate by Travel to Work Areas (TTWAs)

	Unweighted	Weighted by ad count	Weighted by population > 16
Low skill			
log($1 + u_{ttwa}$)	0.107***	-0.018	0.007
	(0.040)	(0.062)	(0.055)
Observations	202	202	202
R2	0.073	0.002	0.000
Middle skill			
log($1 + u_{ttwa}$)	0.161***	0.060***	0.068***
	(0.060)	(0.019)	(0.021)
Observations	201	201	201
R2	0.119	0.043	0.041
High skill			
log($1 + u_{ttwa}$)	0.220**	-0.048	0.011
	(0.095)	(0.056)	(0.049)
Observations	202	202	202
R2	0.116	0.010	0.000

Notes: This table presents estimates of $\beta_{lc,u_{ttwa}}$ in the regression model $log(1+s_{lc,ttwa}) = \beta_{lc,u_{ttwa}} log(1+u_{ttwa})+ \varepsilon_{ttwa}$. $s_{lc,ttwa}$ is the low-carbon share of job ads from 2012-2021 for a given TTWA, and u_{ttwa} is average share of unemployed people aged 16+ between 2012 and 2021 for a given TTWA. Column (1) presents unweighted regression results, column (2) shows results weighted by the number of job ads between 2012 and 2021 in each TTWA, and column (3) shows results weighted by average population in each TTWA between 2012 and 2021. The top panel shows results for low-skill occupations (UK SOC Major groups 6 and above), the middle panel shows results for middle-skill occupations (UK SOC Major groups 4 and 5), and the bottom panel is results for high-skill occupations (UK SOC Major groups 1, 2, and 3). Standard errors are robust. ***p<0.01, **p<0.05, *p<0.1.

Table 7.12: Correlation between the share of low-carbon ads and labour productivity by Travel to Work Areas (TTWAs)

	Unweighted	Weighted by ad count	Weighted by population > 16
Low skill			
log(GVA_{TTWA})	0.002	-0.006***	-0.006***
	(0.002)	(0.001)	(0.001)
Observations	223	223	213
R2	0.005	0.216	0.168
Middle skill			
log(GVA_{TTWA})	0.002	0.001*	0.001
	(0.002)	(0.001)	(0.001)
Observations	221	221	211
R2	0.004	0.011	0.004
High skill			
log(GVA_{TTWA})	0.010***	-0.002	0.000
	(0.004)	(0.001)	(0.002)
Observations	222	222	212
R2	0.052	0.014	0.000

Notes: This table presents estimates of $\beta_{lc,GVA_{ttwa}}$ in the regression model $log(1 + s_{lc,ttwa}) = \beta_{lc,GVA_{ttwa}} log(GVA_{ttwa}) + \varepsilon_{ttwa}$. $s_{lc,ttwa}$ is the low-carbon share of job ads from 2012-2021 for a given TTWA, and GVA_{ttwa} is average gross value added per job between 2012 and 2021 for a given TTWA. Column (1) presents unweighted regression results, column (2) shows results weighted by the number of job ads between 2012 and 2021 in each TTWA, and column (3) shows results weighted by average population in each TTWA between 2012 and 2021. The top panel shows results for low-skill occupations (UK SOC Major groups 6 and above), the middle panel shows results for middle-skill occupations (UK SOC Major groups 4 and 5), and the bottom panel is results for high-skill occupations (UK SOC Major groups 1, 2, and 3). Standard errors are robust. ***p<0.01, **p<0.05, *p<0.1.

Table 7.13: Job vacancies by region and skill level

	Unweighted Ad Count			Unweighted Ad Share		
	Low skill	Middle skill	High skill	Low skill	Middle skill	High skill
East Midlands						
Generic	2,221,686	1,044,223	645,548	98.64%	99.05%	98.93%
High Carbon	345	447	111	0.02%	0.04%	0.02%
Low Carbon	30,390	9,619	6,872	1.35%	0.91%	1.05%
East Of England						
Generic	3,402,662	1,405,586	928,363	98.98%	99.08%	99.09%
High Carbon	693	503	118	0.02%	0.04%	0.01%
Low Carbon	34,382	12,545	8,419	1.00%	0.88%	0.90%
London						
Generic	10,173,982	1,987,173	1,530,615	98.93%	99.31%	98.91%
High Carbon	2,644	996	246	0.03%	0.05%	0.02%
Low Carbon	106,929	12,806	16,597	1.04%	0.64%	1.07%
North East						
Generic	817,368	376,082	210,542	98.69%	98.94%	98.83%
High Carbon	387	136	41	0.05%	0.04%	0.02%
Low Carbon	10,495	3,895	2,451	1.27%	1.02%	1.15%
North West						
Generic	3,513,826	1,422,495	844,984	98.85%	98.98%	98.96%
High Carbon	687	507	201	0.02%	0.04%	0.02%
Low Carbon	40,180	14,166	8,651	1.13%	0.99%	1.01%
Northern Ireland						
Generic	580,052	218,886	164,729	99.12%	99.29%	99.33%
High Carbon	20	111	20	0.00%	0.05%	0.01%
Low Carbon	5,118	1,451	1,084	0.87%	0.66%	0.65%
Scotland						
Generic	2,172,444	905,913	606,039	98.03%	98.66%	98.70%
High Carbon	3,809	558	428	0.17%	0.06%	0.07%
Low Carbon	39,798	11,769	7,539	1.80%	1.28%	1.23%
South East						
Generic	6,160,947	2,313,511	1,541,779	98.98%	99.24%	99.08%
High Carbon	2,185	923	416	0.04%	0.04%	0.03%
Low Carbon	61,414	16,861	13,952	0.99%	0.72%	0.90%
South West						
Generic	2,981,285	1,217,386	800,800	98.71%	98.97%	98.89%
High Carbon	577	513	205	0.02%	0.04%	0.03%
Low Carbon	38,306	12,107	8,820	1.27%	0.98%	1.09%
Wales						
Generic	871,995	401,834	226,948	98.75%	98.92%	98.79%
High Carbon	163	219	80	0.02%	0.05%	0.03%
Low Carbon	10,890	4,178	2,692	1.23%	1.03%	1.17%
West Midlands						
Generic	3,537,923	1,344,817	912,319	98.68%	99.03%	99.00%
High Carbon	350	470	166	0.01%	0.03%	0.02%
Low Carbon	46,856	12,732	9,070	1.31%	0.94%	0.98%
Yorkshire And The Humber						
Generic	2,397,402	962,470	635,037	98.84%	98.86%	99.00%
High Carbon	534	379	64	0.02%	0.04%	0.01%
Low Carbon	27,594	10,756	6,329	1.14%	1.10%	0.99%

Notes: The table shows the number of vacancies across 2012-2021 by region, skill level, and carbon category (generic, high-carbon, and low-carbon), as well as the ad share for each carbon category within each region and skill level). All statistics are unweighted and calculated directly from the Lightcast data.

Table 7.14: Low-carbon wage gap regression results by occupation group

	Main specification				Control for industry			
	Weighted		Unweighted		Weighted		Unweighted	
	2012-2015	2018-2021	2012-2015	2018-2021	2012-2015	2018-2021	2012-2015	2018-2021
211 - Natural and social science professionals								
Job ad is low carbon	-0.036*	-0.033**	-0.024	-0.024	-0.023***	-0.001	-0.013	0.000
	(0.013)	(0.008)	(0.032)	(0.014)	(0.004)	(0.003)	(0.016)	(0.004)
Total ads	61,307	89,816	61,307	89,816	38,368	60,488	38,368	60,488
Low carbon ads	2,682	3,659	2,682	3,659	1,491	2,341	1,491	2,341
R2	0.36	0.34	0.35	0.34	0.31	0.31	0.31	0.31
212 - Engineering professionals								
Job ad is low carbon	0.053***	0.007	0.051***	0.017	0.061***	-0.006	0.058***	-0.003
	(0.008)	(0.021)	(0.009)	(0.018)	(0.009)	(0.015)	(0.009)	(0.017)
Total ads	421,478	383,518	421,478	383,518	88,162	86,345	88,162	86,345
Low carbon ads	26,795	21,091	26,795	21,091	6,089	5,815	6,089	5,815
R2	0.39	0.36	0.39	0.36	0.42	0.38	0.42	0.37
243 - Architects, town planners and surveyors								
Job ad is low carbon	0.057	0.012	0.055	0.003	0.041	-0.002	0.042	-0.005
	(0.051)	(0.016)	(0.046)	(0.019)	(0.052)	(0.007)	(0.049)	(0.011)
Total ads	149,832	174,804	149,832	174,804	40,157	46,538	40,157	46,538
Low carbon ads	7,978	5,259	7,978	5,259	2,263	1,714	2,263	1,714
R2	0.37	0.35	0.37	0.35	0.36	0.36	0.36	0.36
311 - Science, engineering and production technicians								
Job ad is low carbon	0.092**	0.028	0.121**	0.058	0.090***	-0.013	0.103***	0.019
	(0.027)	(0.028)	(0.040)	(0.037)	(0.013)	(0.031)	(0.019)	(0.038)
Total ads	253,463	361,151	253,463	361,151	79,043	119,606	79,043	119,606
Low carbon ads	8,149	10,240	8,149	10,240	2,413	3,786	2,413	3,786
R2	0.42	0.35	0.42	0.35	0.42	0.34	0.42	0.34
52 - Skilled metal, electrical and electronic trades								
Job ad is low carbon	0.078***	0.008	0.088***	0.028	0.078***	-0.019	0.085***	-0.001
	(0.016)	(0.020)	(0.016)	(0.028)	(0.014)	(0.033)	(0.018)	(0.036)
Total ads	298,337	388,603	298,337	388,603	110,971	154,514	110,971	154,514
Low carbon ads	6,688	10,571	6,688	10,571	2,317	3,873	2,317	3,873
R2	0.37	0.28	0.37	0.28	0.40	0.27	0.39	0.27
53 - Skilled construction and building trades								
Job ad is low carbon	0.149***	0.051**	0.150***	0.035	0.159***	0.049***	0.158***	0.026
	(0.015)	(0.021)	(0.013)	(0.023)	(0.037)	(0.013)	(0.037)	(0.024)
Total ads	93,198	145,638	93,198	145,638	46,840	76,566	46,840	76,566
Low carbon ads	3,702	4,508	3,702	4,508	1,467	1,958	1,467	1,958
R2	0.37	0.29	0.37	0.29	0.36	0.28	0.36	0.28
81 - Process, plant and machine operatives								
Job ad is low carbon	0.185***	0.101	0.217***	0.143**	0.203***	0.064**	0.195***	0.086***
	(0.049)	(0.065)	(0.052)	(0.059)	(0.024)	(0.031)	(0.027)	(0.015)
Total ads	100,455	154,170	100,455	154,170	26,577	41,086	26,577	41,086
Low carbon ads	2,997	3,521	2,997	3,521	1,273	1,460	1,273	1,460
R2	0.39	0.34	0.39	0.33	0.42	0.34	0.41	0.34
82 - Transport and mobile machine drivers and operatives								
Job ad is low carbon	0.057	-0.032	0.070**	0.000	0.042	-0.034**	0.045	0.001
	(0.039)	(0.030)	(0.031)	(0.033)	(0.053)	(0.012)	(0.046)	(0.035)
Total ads	170,101	296,597	170,101	296,597	109,229	193,034	109,229	193,034
Low carbon ads	5,723	16,736	5,723	16,736	4,197	14,614	4,197	14,614
R2	0.28	0.25	0.28	0.25	0.26	0.24	0.26	0.23
Fixed effects								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TTWA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4-digit SOC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC2	No	No	No	No	Yes	Yes	Yes	Yes

Notes: This table presents detailed results for the low-carbon wage gap analysis by occupation group and sample period. "Job ad is low-carbon" indicates the coefficient estimate on a dummy variable that indicates whether or not a job ad is low-carbon, so the estimate reflects the average difference in wages for low-carbon job ads versus all other job ads within the occupation group. All specifications control for year, TTWA, and 4-digit SOC fixed effects, and specifications under the "Control for industry" columns also include fixed effects for 2-digit SIC codes. "Weighted" specifications use ONS Labour Force Survey total number of persons employed by 4-digit SOC as regression weights. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 7.15: High-carbon wage gap regression results by occupation

	Main specification				Control for industry			
	Weighted		Unweighted		Weighted		Unweighted	
	2012-2015	2018-2021	2012-2015	2018-2021	2012-2015	2018-2021	2012-2015	2018-2021
212 - Engineering professionals								
Job ad is high carbon	0.253***	0.071***	0.247***	0.087**	-0.038	0.055	-0.038	0.055
	(0.039)	(0.018)	(0.038)	(0.028)	(0.042)	(0.038)	(0.042)	(0.038)
Total ads	421,478	383,518	421,478	383,518	88,162	86,345	88,162	86,345
High carbon ads	3,240	1,271	3,240	1,271	3,240	1,271	3,240	1,271
R2	0.39	0.36	0.39	0.36	0.42	0.37	0.42	0.37
53 - Skilled construction and building trades								
Job ad is high carbon	0.113***	-0.023	0.111***	-0.017	-0.060	0.001	-0.060	0.001
	(0.030)	(0.014)	(0.027)	(0.012)	(0.052)	(0.022)	(0.052)	(0.022)
Total ads	93,198	145,638	93,198	145,638	46,840	76,566	46,840	76,566
High carbon ads	379	890	379	890	379	890	379	890
R2	0.37	0.29	0.37	0.29	0.37	0.28	0.37	0.28
81 - Process, plant and machine operatives								
Job ad is high carbon	0.144	0.261***	0.269*	0.170	-0.136	0.130	-0.136	0.130
	(0.125)	(0.089)	(0.134)	(0.152)	(0.187)	(0.159)	(0.187)	(0.159)
Total ads	100,455	154,170	100,455	154,170	26,577	41,086	26,577	41,086
High carbon ads	732	2,157	732	2,157	332	821	332	821
R2	0.39	0.34	0.39	0.34	0.42	0.34	0.42	0.34
Fixed effects								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TTWA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4-digit SOC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC2	No	No	No	No	Yes	Yes	Yes	Yes

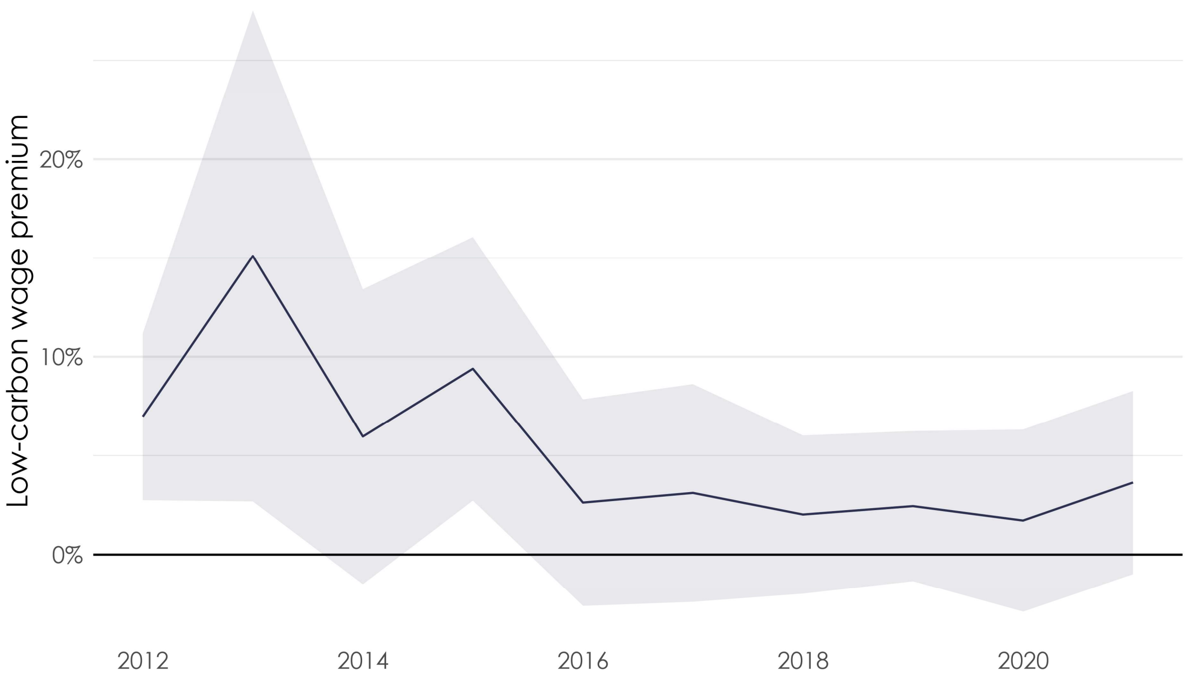
Notes: This table presents detailed results for the high-carbon wage gap analysis by occupation group and sample period. "Job ad is high-carbon" indicates the coefficient estimate on a dummy variable that indicates whether or not a job ad is high-carbon, so the estimate reflects the average difference in wages for high-carbon job ads versus all other job ads within the occupation group and during the sample period indicated in the column header. All specifications control for year, TTWA, and 4-digit SOC fixed effects, and specifications under the "Control for industry" columns also include fixed effects for 2-digit SIC codes. "Weighted" specifications use ONS Labour Force Survey total number of persons employed by 4-digit SOC as regression weights. ***p<0.01, **p<0.05, *p<0.1.

Table 7.16: Full sample low-carbon wage gap regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job ad is low carbon	0.101***	0.059***	0.059***	0.060***	0.055***	0.046***	0.048***
	(0.028)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Degree							0.247***
							(0.039)
Experience							0.060***
							(0.009)
Experience squared							-0.003***
							(0.001)
Observations	18,013,593	18,013,189	18,013,189	18,013,189	15,994,637	10,817,168	479,970
RMSE	0.406	0.376	0.367	0.367	0.366	0.369	0.343
Fixed effects							
Year	YES	YES	YES	YES	YES	YES	YES
1-digit SOC	YES						
4-digit SOC		YES	YES	YES	YES	YES	YES
TTWA			YES	YES	YES	YES	YES
Skill vector length bins				YES	YES	YES	YES
2-digit industry					YES		YES
3-digit industry						YES	

Notes: This table presents estimates of the average wage premium for low-carbon versus all other jobs across all sample years (2012-2021) and occupations. Moving right to left across the table, each column includes a progessively more strict set of fixed effects. The specification in column (1) includes year and 1-digit SOC fixed effects; column (2) uses 4-digit SOC fixed effects; column (3) adds Travel to Work Area (TTWA) fixed effects; column (6) adds fixed effects for 5 bins for the number of skills in the job ad (the bins are 1-2, 3-4, 5-6, 7-8, and 9+ skills); column (5) adds 2-digit SIC fixed effects; column (6) uses 3-digit SIC fixed effects instead; column (7) adds controls for degree and experience requirements. All regressions are weighted by ONS Labour Force Survey count of number of persons employed at the 4-digit SOC level. Standard errors are clustered by 1-digit SOC for column (1), and clustered by 4-digit SOC for all other columns. ***p<0.01, **p<0.05, *p<0.1.

Figure 7.10: Full sample low-carbon wage premium by year



Notes: This figure illustrates estimates of the average low-carbon wage premium for each sample year across the full sample of occupations. The estimate reflects the average wage differential for low-carbon versus all other job ads, controlling for TTWA, 4-digit SOC, and 2-digit SIC fixed effects. Regressions are weighted by ONS Labour Force Survey total number of persons employed by 4-digit SOC.

Table 7.17: Correlation between low-carbon ad share and average salary by 4-digit SOC

	Full sample	High skill	Low skill	Middle skill
Log of (1 + low-carbon ad share)	0.318	1.373	0.216	4.407***
	(0.639)	(1.308)	(0.361)	(1.383)
Observations	362	106	176	80
R2	0.002	0.009	0.002	0.204

Notes: We regress the log of 1 + the (weighted) share of low-carbon ads across 2012-2021 on the log of average salary across 2012-2021 at the 4-digit SOC level. Regressions are weighted by average LFS employment count across the sample period. Standard errors are robust. ***p<0.01, **p<0.05, *p<0.1.

Figures for US analysis

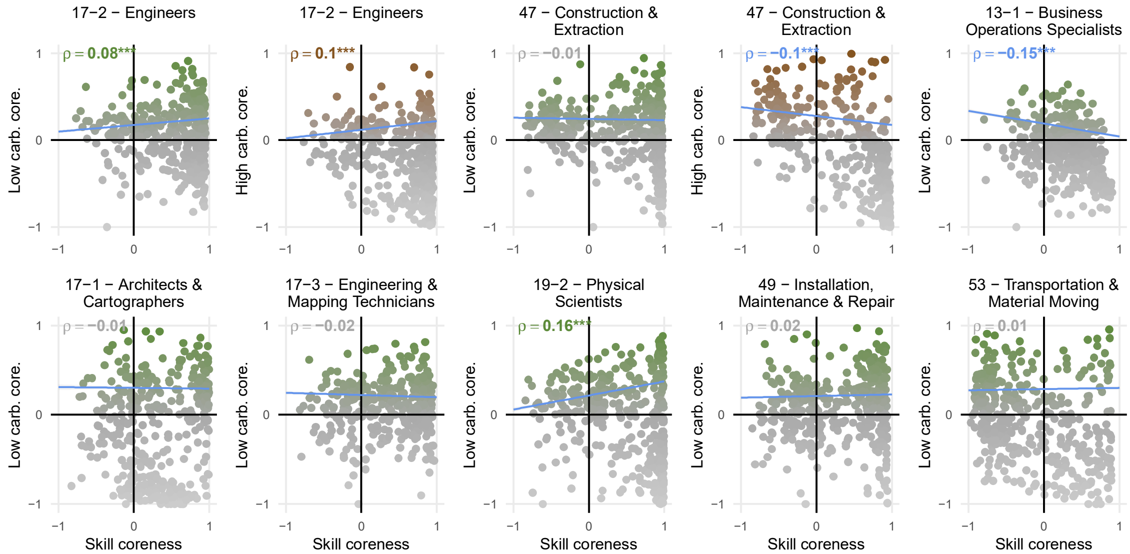
Figure 7.11: Evolution of low-carbon ads in the US (2010-2019)

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.

Figure 7.12: US Differences in broad skills by occupation

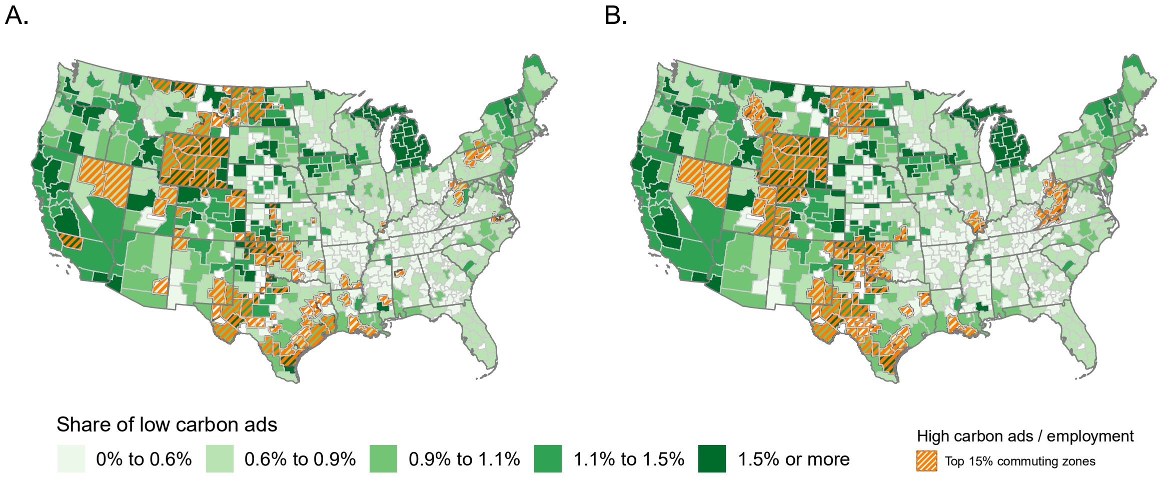
Notes: Each panel represents the share of ads for a given occupation and category (generic, low- or high-carbon) that contains *exactly one* (1) or *two or more* (2+) skills pertaining to any of the five broad skill categories listed. Percentages reported correspond to unweighted shares of ads obtained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

Figure 7.13: Specialisation versus diversification by occupation



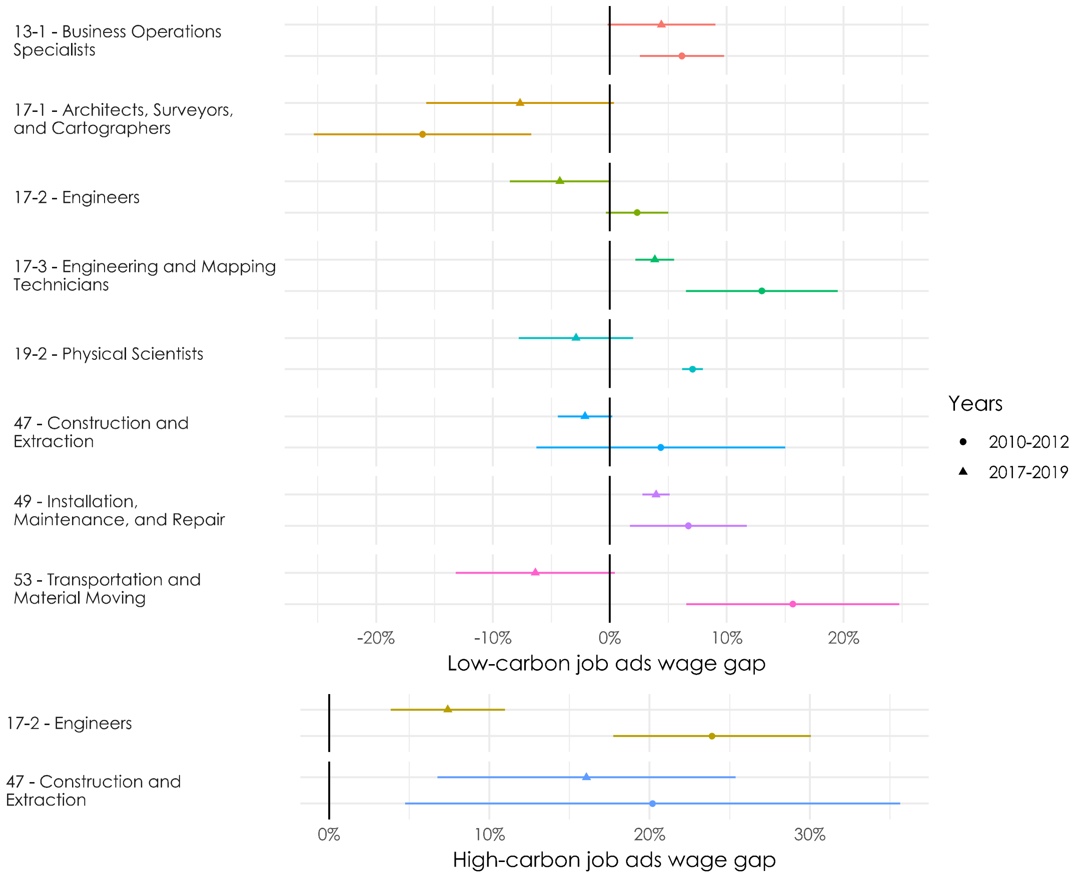
Notes: Relationship between the relative prevalence of a given skill in low- (resp. high-) carbon ad – low- (resp. high-) carbon-coreness on the y axis – and its relative prevalence in the entire sample – skill coreness, x axis (see formulas in the appendix of Saussay et al. (2022) for a precise definition). 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. ***p<0.01, **p<0.05, *p<0.1.

Figure 7.14: 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 Popp et al. (2021) from the BLS's Occupational Employment and Wage Statistics).

Figure 7.15: US 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.