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Virtual Seminar on Climate Economics

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

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Policy objective to create jobs through climate mitigation

President Obama's 2008 campaign sought to create **"5 million 'green' jobs"**

President Biden promises that his focus on environment will be **"jobs, jobs, jobs"**

Mitigation requires shifting away from fossil industries

Phasing out fossil fuels **jeopardizes** the **livelihood** of **communities** that depend of **fossil-fuel extraction** and fossil-intensive **industries**

Low carbon jobs are difficult to observe unlike 'dirty' jobs

- Widespread across sectors, occupations, geography
- New, and changing

⇒Lack of agreed definition, classification and data

- Concentrated
- Well established

Public debate exaggerates the **job killing argument** while downplaying the **job creation** effect of the **low-carbon transition**

How to define green job and green skills?

- **No agreed definition** of green jobs or green skills
  - Green sectors? Green firms? Green activities? Green workers?
- A **working definition** of **green jobs** needs to **account** for the **skills profile** of green jobs
- Why focus on **green skills**?
  - Evaluate the **skill gap** between **newly created green jobs** and **jobs destroyed** by **environmental regulation** (brown jobs) to evaluate the **possibility** of **re-employing** displaced workers
  - Consider the need of **complementary educational** and **training policies** to be combined with environmental policies

BLS Green Jobs Initiative (2010)

- **BLS program** initiated in 2010 to help measure for **green jobs**:
  - **Number** of and **trend** over time
  - **Industrial**, **occupational**, and **geographic distribution**
  - **Wages**
- **Output** approach: who produces green **goods**?
- **Process** approach: who uses green **processes**?
- **O*NET Green Task Development Project** (2010) identified:
  - **1,369 green tasks**
  - Added green tasks to **105 existing occupations**
  - **33** new and emerging green **occupations**

Combining task-based approach with the O*NET dataset

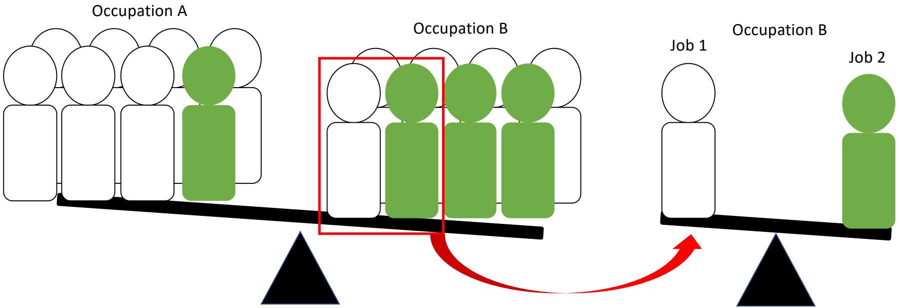
- First **data driven** methodology
- Measure **occupation level** exposure to green technologies and productions: **share of green tasks** over total tasks (Vona et al., 2018, 2019)
- Data-driven identification of **green skills** (Vona et al., 2018) and assessing direct and indirect green jobs (multiplier effects) (Bowen et al., 2018; Vona et al., 2019)
- Using **exogenous policy variation** to examine the effect of policies on demand for green skills (Vona et al., 2018; Popp et al., 2021; Marin and Vona, 2019; Vona et al., 2019)

Key insights gained

- **Green** occupations require **more on the job training** are slightly **more non-routine** cognitive than non-green occupations (Consoli et al., 2016)
- Green occupations require **more technical**, **engineering**, **monitoring** and **managerial** skills. (Vona et al., 2018)
- **Winners** (**technicians**, **engineers**) and **losers** (**manual workers**) from the green transition (Marin and Vona, 2019)
- Effect of **green subsidies** strongly mediated by the **local availability** of **green skills** (Popp et al., 2021)

- **Limitations** of the **O*NET** data on green jobs (i.e., Green Economy Program)
  - Can't precisely observe green jobs **within an occupation**
  - Difficult to conduct **more granular analysis** for specific technologies or occupations
  - Data updated **infrequently**

Going more granular



Our approach: Skill-based, using **job** level data

- **Advantages of job level data**
  - Move from occupational level to **job level** data on skill profiles
  - Examine **skills gaps within an occupational group**
- **Lightcast** dataset comprising **all job advertisements in the United States** over 2010-2019
  - **196 million** job ads
  - **Occupation**
  - **Skills required**
  - **Salary** offered
  - **Education** requirements
- Workers more likely to **transition** towards green jobs within the **same occupational group**

Relation to the literature

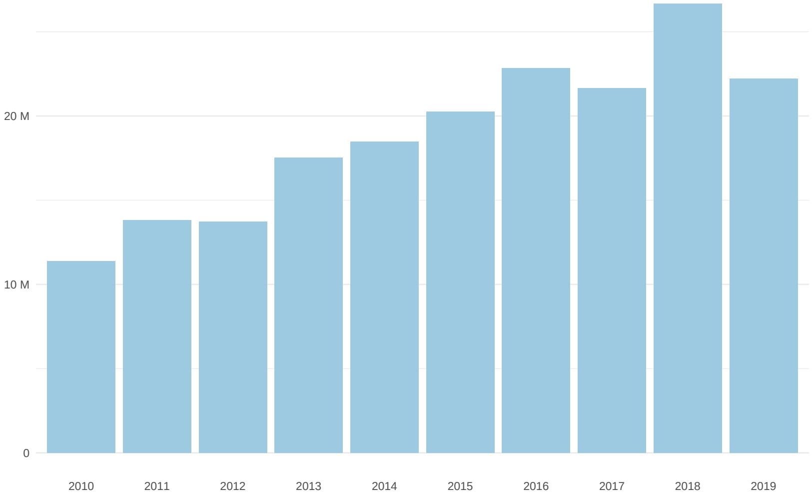
- **Identifying green jobs**
  Vona et al. (NBER 2015); Vona et al. (JAERE, 2018); Bowen et al. (EE, 2018); Vona et al. (JEconGeo, 2019); Curtis & Marinescu (NBER, 2022)

- **Labour market impacts of environmental policies**
  Greenstone (JPE, 2002); Kahn & Mansur (JPubE, 2013); Hafstead & Williams (JPubE 2018); Marin et al. (ERE, 2018); Castellanos & Heutel (NBER, 2019); Marin & Vona (JEEM, 2019)

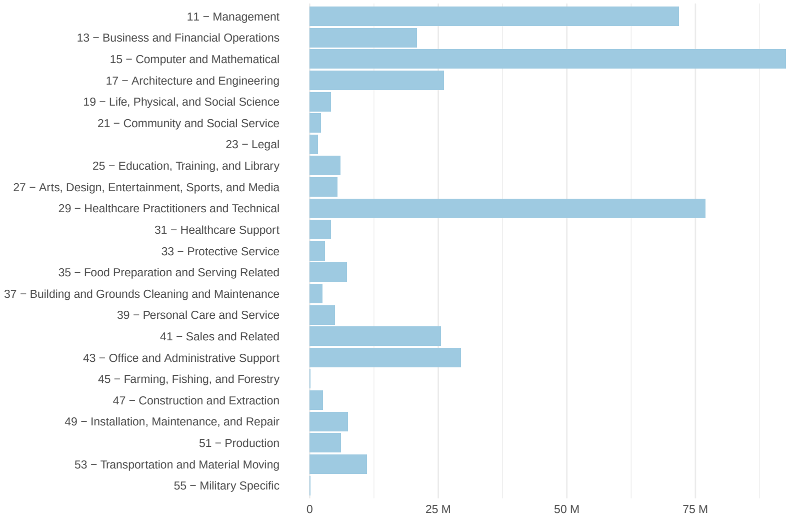
- **Labour market adjustments to technological change**
  Hershbein & Kahn (AER, 2018); Deming & Kahn (JLE, 2018); Gathmann & Schoenberg (JLE, 2010); Atalay et al., (AEJ: AE, 2018)

The Lightcast dataset

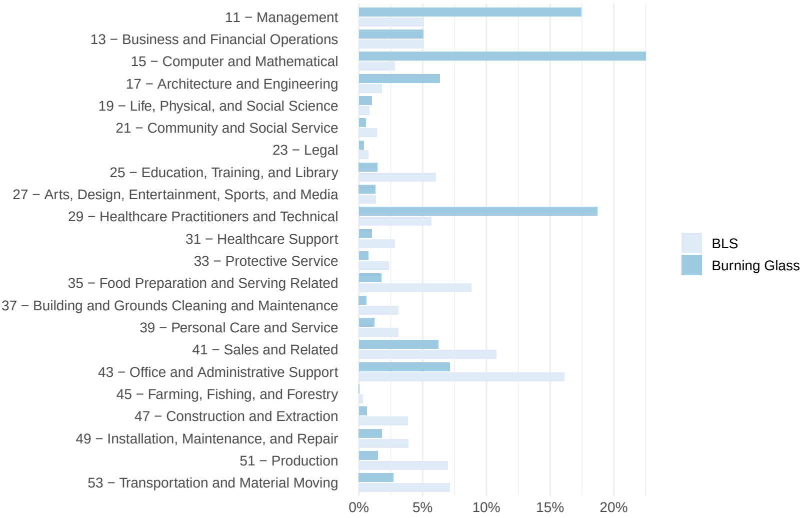
Number of ads collected has doubled since 2010



Total job ads across occupations (SOC major groups)



High skilled occupations are over-represented



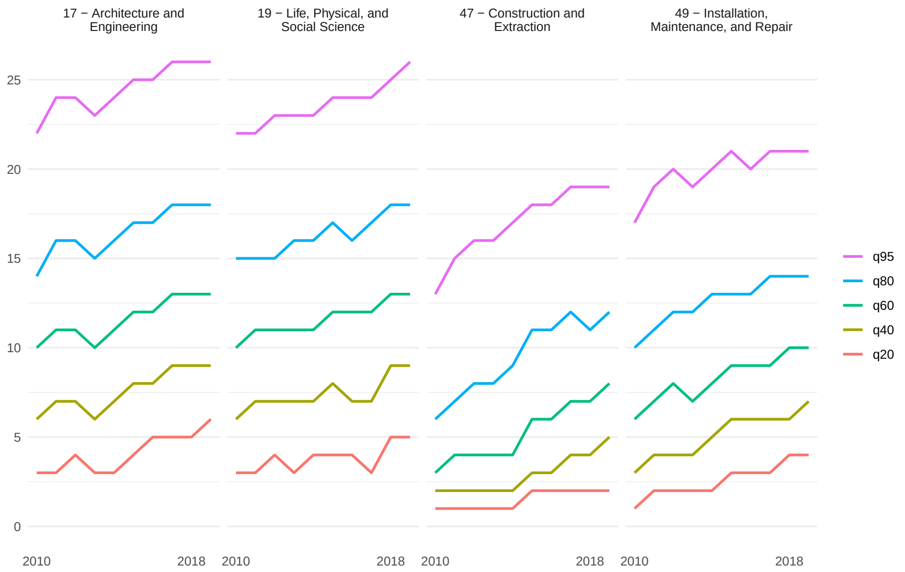
What's in an ad?

- Example: Chemical Engineer job offered in Sunnyvale, CA in 2018
  - MSc required
  - 3 years of experience
  - Starts at $118k
- Job ads are represented as a set of *skills*

Cost Control	Project Management	Quality Assurance and Control
Fuel Cell	Process Engineering	Biotechnology
Six Sigma	Machine Operation	Manufacturing Processes
Biotechnology Product Development	Genetic Testing	Logistics

- BG reports more than 16,000 distinct skills
- We apply **Natural Language Processing** (NLP) and **expert elicitation** to identify **green skills**

Highly heterogeneous skill vector length across occupations



Identifying low carbon skills

Identifying core low carbon skills

- Need to identify **skills** that are characteristic of the **core low carbon** (climate-related) occupations

Keywords source → NLP → Expert survey → Core low carbon skills

  - Obtain **source text** from which to extract **low carbon keywords**
  - **Green tasks** associated with **climate-related** occupations in **O*NET** (subset of Green Economy)
    - *"Calculate potential for energy savings."*
    - *"Fabricate prototypes of fuel cell components, assemblies, or systems."*
    - *"Test wind turbine components, by mechanical or electronic testing."*
  - **Green products** descriptions from **PRODCOM**

Identifying core low carbon skills

- Need to identify **skills** that are characteristic of the **core low carbon** (climate-related) occupations

Keywords source → **NLP** → Expert survey → Core low carbon skills

  - Use **natural language processing** to extract **low carbon keywords**
  - **Unsupervised machine learning** using **TF-IDF**
  - **Semantically matched** against BG skills using **word embeddings** (Word2Vec)
  - Yields a **"greeness" score** between 0 and 1
  - **Perfect semantic matches** against **top 20 keywords** are considered **core low carbon**: **396 skills**

Identifying core low carbon skills

- Need to identify **skills** that are characteristic of the **core low carbon** (climate-related) occupations

Keywords source → NLP → **Expert survey** → Core low carbon skills

  - High scoring skills are potentially core low carbon, but must be **inspected manually**
  - **Supervised** portion of our selection algorithm
  - **Surveyed 60+ experts** from LSE, Oxford, OECD, University of Venice among others to review 600 high scoring skills
  - **51** skills were selected

Identifying core low carbon skills

- Need to identify **skills** that are characteristic of the **core low carbon** (climate-related) occupations

Keywords source → NLP → Expert survey → **Core low carbon skills**

- **447 core low carbon skills**
  - *"Solar Energy Components"*
  - *"Wind Energy Engineering"*
  - *"Light Rail Transit Systems"*
  - *"Clean Air Act"*
- Each of the 16,000 skills is classified as **low carbon** (climate-related) or **generic**

What's in an ad? Green skill edition

- Example: Chemical Engineer job offered in Sunnyvale, CA in 2018
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Cost Control	Project Management	Quality Assurance and Control
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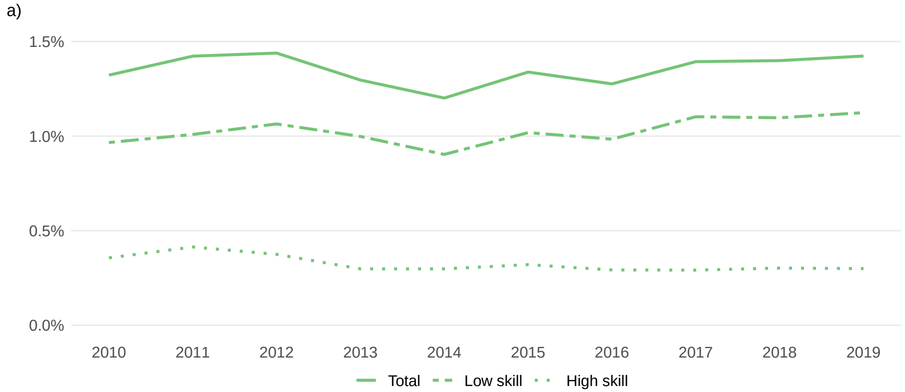
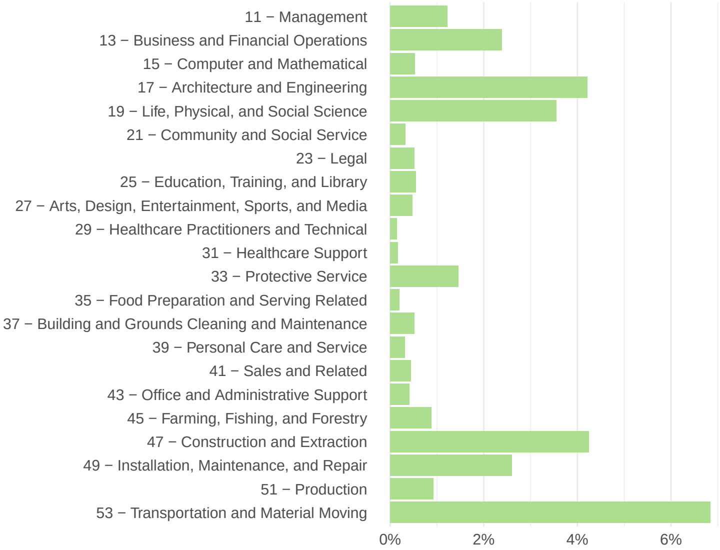
Results

Low carbon jobs' share has not increased since 2010

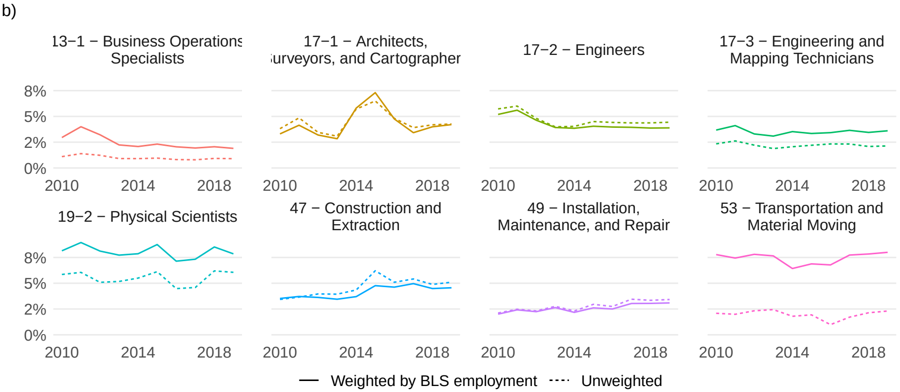


Low carbon ads are concentrated in 6 major SOC groups



Share of low-carbon ads by occupation (2010-2019)

Evolution of low carbon share across occupations



Skill gaps are larger and broader in high-skilled occupations

Heterogeneous skills gap in low-skilled occupations

Specialization vs diversification by occupation

- Define low and high-carbon **skill coreness indices**:

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

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

where n_s^{SOC} is the number of ads requiring skill s in occupational group SOC

n^{SOC} is the number of ads in occupational group SOC

n_s is the number of ads requiring skill s in the entire sample

n is the total number of ads in the sample

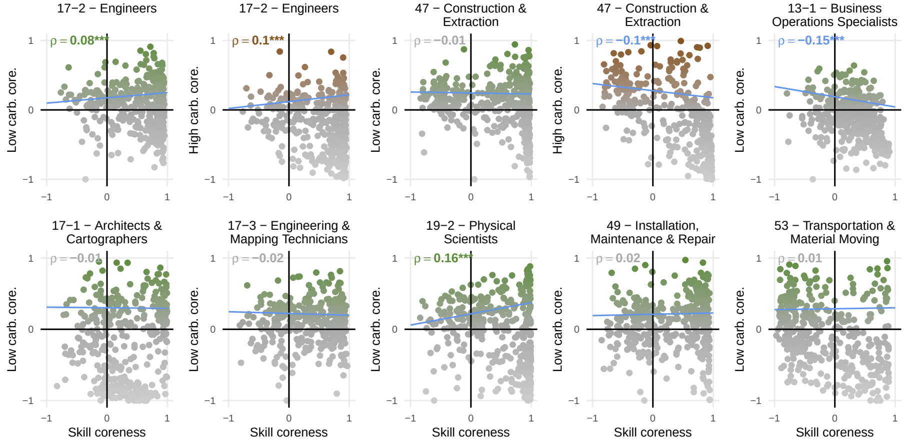
$n_s^{c,SOC}$ is the number of low (resp. high) carbon ads requiring skill s in occupational group SOC

$n^{c,SOC}$ is the number of low (resp. high) carbon ads in occupational group SOC

n_s^{SOC} is the number of ads requiring skill s in occupational group SOC

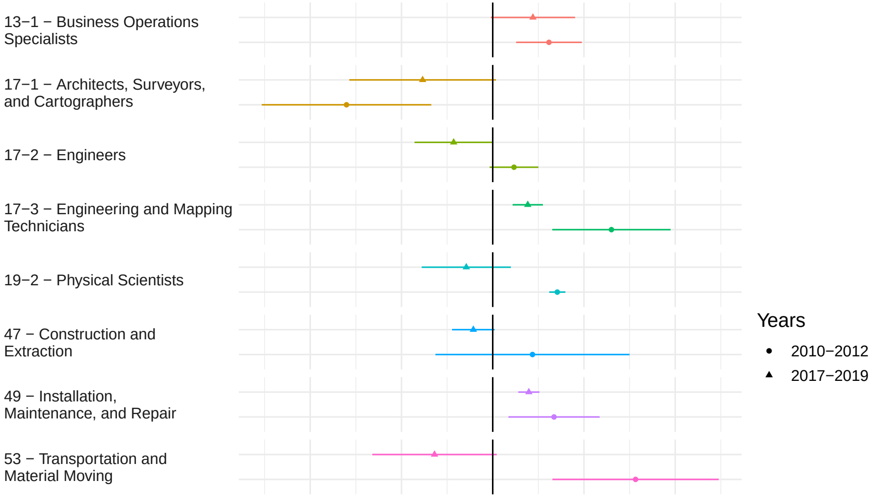
n^{SOC} is the number of ads in occupational group SOC

Specialization vs diversification by occupation

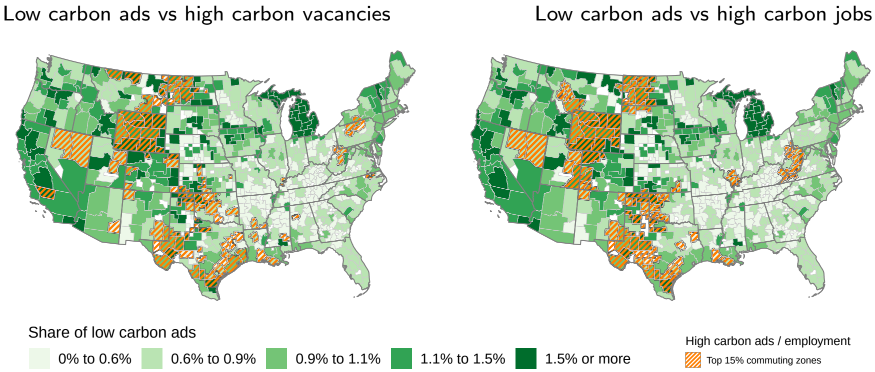


Specialization vs diversification by occupation

The green wage premium has vanished over the decade



Limited overlap between low and high-carbon low-skilled jobs



Low carbon jobs are created in relatively richer areas

Table SI.14: Correlation between the share of low-carbon ads and annual personal income

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

Table SI.15: Correlation between the share of high-carbon ads and annual personal income

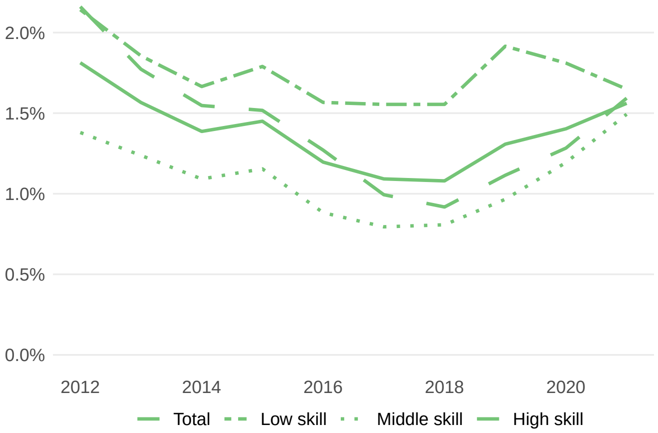
	Low skill		
	Unweighted	Weighted by ad count	Weighted by population
$\log(inc_{cz})$	0.007***	−0.001**	−0.001***
	(0.002)	(0.000)	(0.000)
Observations	647	647	647
R2	0.03	0.01	0.01
AIC	−4.522	−4.456	−4.459

Conclusions

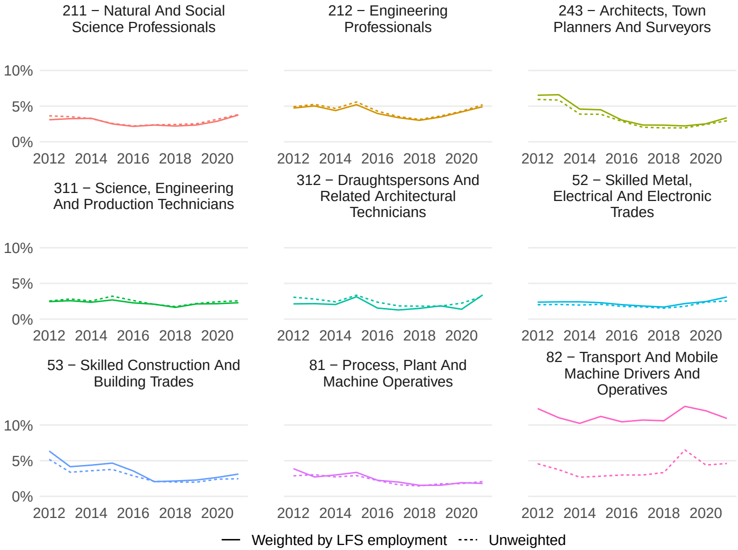
- **No increase** in the **overall demand for low carbon jobs** over the **past decade** in the **US**
  - **Increase** in **low skill** occupations, **decrease** in **high skill** occupations
- **Low carbon jobs require more skills**
  - Skill gap more pronounced in **high-skilled** occupations, and for **social**, **management**, and **technical** skills
  - Emerging skill gap **larger** and **broader** than previously considered
- The low carbon **wage premium** has **eroded over time**
- **Lack** of a **wage premium** for low carbon jobs despite **higher skills** requirements is problematic for their **attractiveness**
- **Powerful**, **replicable** tool to **monitor**, **evaluate** many aspects of **labour market consequences** of the **low-carbon transition**

Follow-up: UK extension

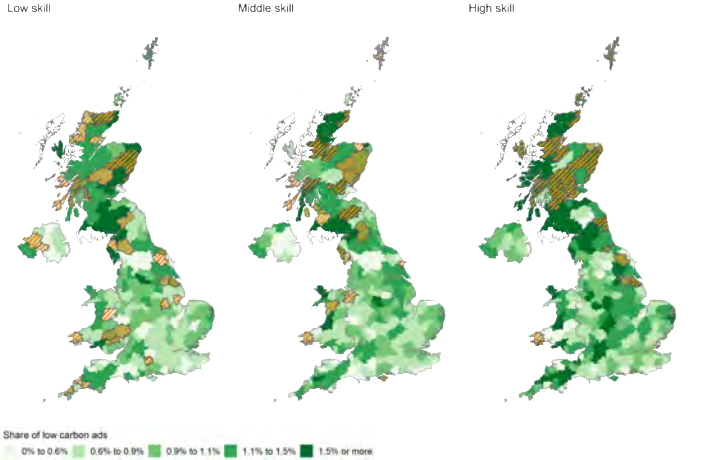
Low carbon ad share: similar to US levels, but different trends



Low carbon share for selected SOC groups

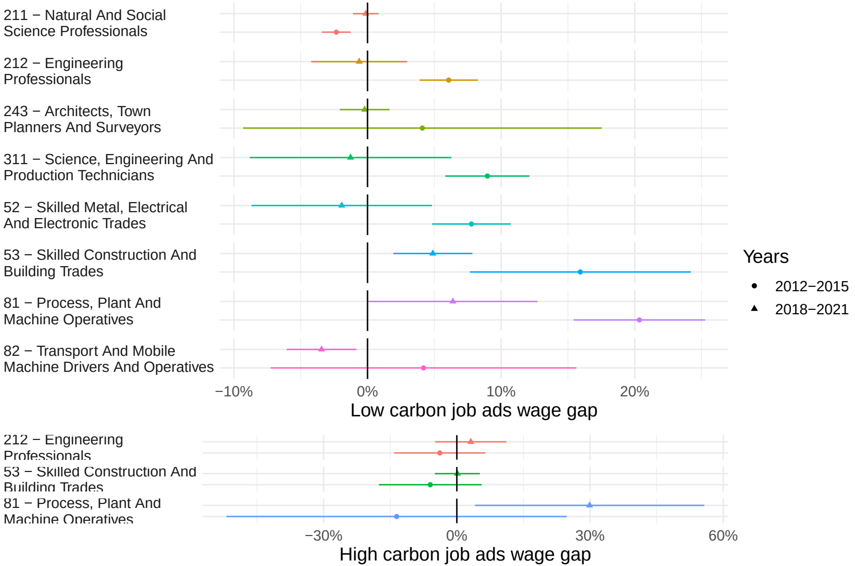


Spatial patterns: Low carbon job ad share



Notes: For each Travel to Work Area (TTWA), we calculate the (unweighted) average of low carbon ad shares across all 4-digit SOC occupations within each skill category. TTWAs approximate local labour market areas. The TTWAs with hashed orange overlay indicates those with a high share (top 15%) of high carbon job ads for that skill level. High skill occupations are those in 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, 7, 8, and 9.

Low carbon wage gap by SOC group



Key Takeaways - UK

1. Low carbon jobs **declined** between 2012-2018 as **green policies** were **killed off** (e.g. onshore wind support, green investment bank, green deal, zero carbon homes)
2. **Growth** in **middle** and **high skilled** low carbon jobs since 2018 but **not low skilled**
3. **Spatial correlation** between **high** and **low carbon jobs**, especially for low skilled but also for high skilled (Scotland)
4. **Green wage premium** has generally **disappeared** in recent years. Some exceptions e.g. Managers and directors (high), skilled construction trade (middle), machine operatives (low)
5. Both green and brown jobs require **more skills than generic jobs**, across all broad skill groups

Appendix

What's in an ad?

- Example: Chemical Engineer job offered in Sunnyvale, CA in 2018
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- Job ads are represented as a set of *skills*

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References I

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