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

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Low carbon jobs are difficult to observe unlike ‘dirty’ jobs

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

$\Rightarrow$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**

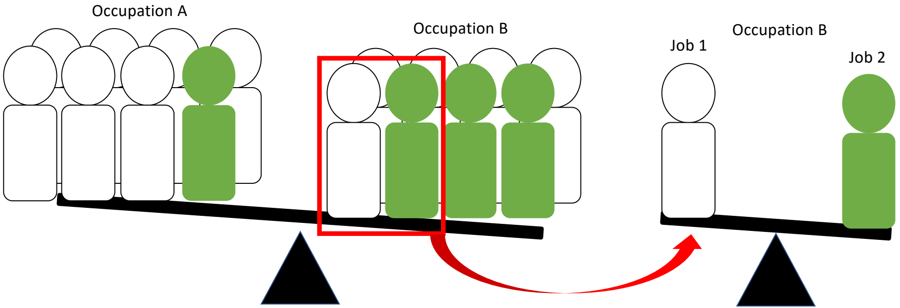
How to define green job and green skills?

- **No agreed definition** of green jobs or green skills
  - Green sectors? Green firms? Green activities? Green workers?
- **Output** approach: who produces green **goods**?
- **Process** approach: who uses green **processes**?
- 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

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)
- **Limitations** of the **O*NET** data on green jobs
  - Can't precisely observe green jobs **within an occupation**
  - Difficult to conduct **more granular analysis**
  - Data updated **infrequently**

Going more granular

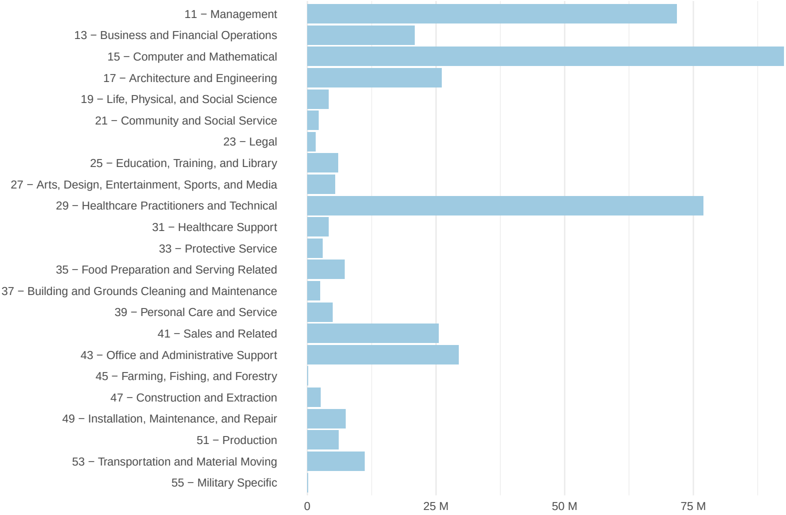


Our approach: Skill-based, using **job** level data

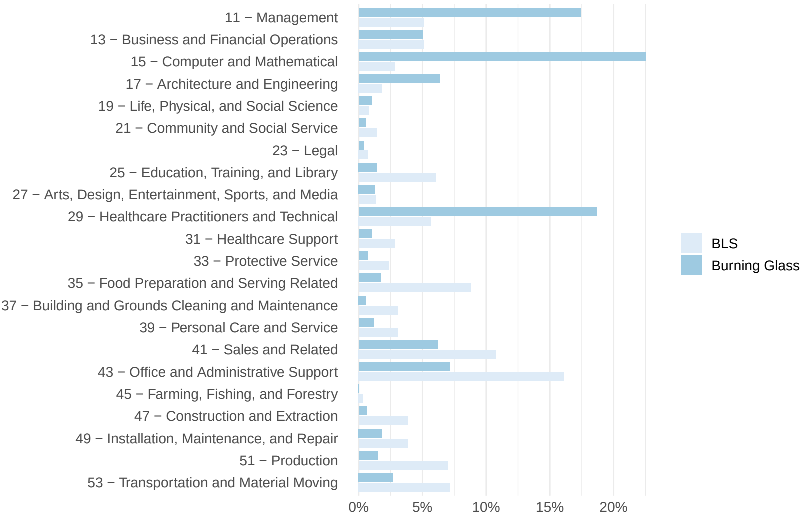
- **Advantages of job level data**
  - Move from occupational level to **job level** data on skill profiles
  - Examine **skills gaps within an occupational group**
- **Lightcast** dataset comprising **all job advertisements in the United States** over 2010-2019
  - **196 million** job ads
  - **Occupation**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

The Lightcast dataset

Total job ads across occupations (SOC major groups)



High skilled occupations are over-represented



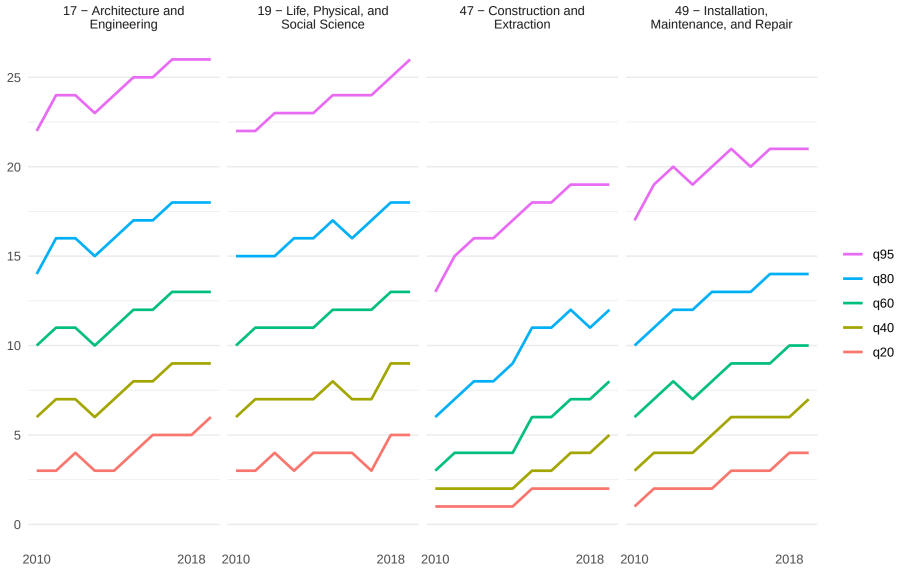
What's in an ad?

- 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**

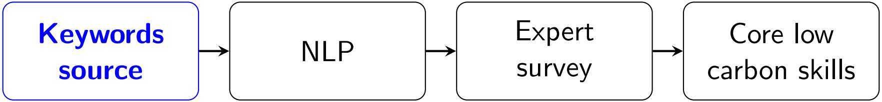
Highly heterogeneous skill vector length across occupations



Identifying low carbon skills

Identifying core low carbon skills

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



  - 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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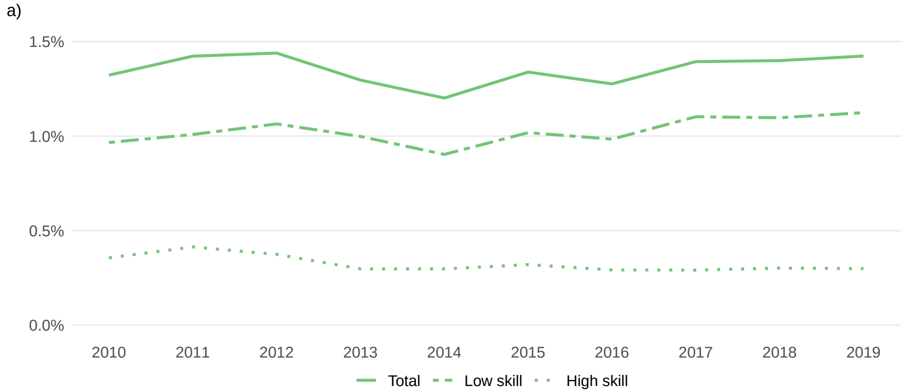
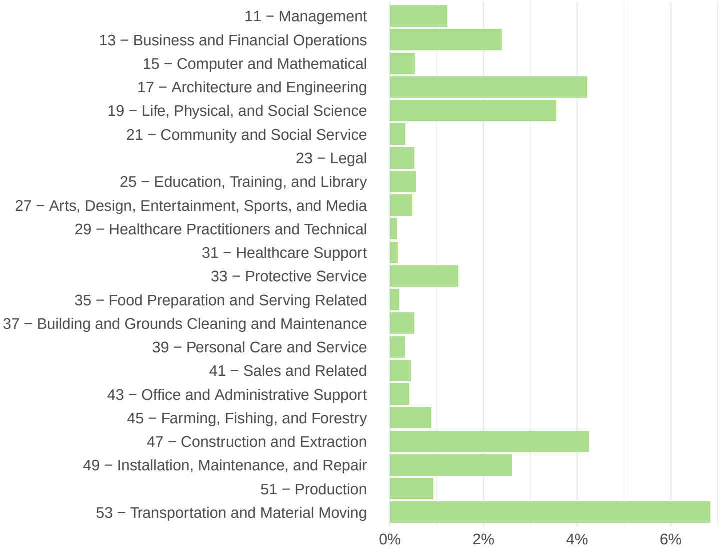
Results

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)

Skill gaps are larger and broader in high-skilled occupations

Heterogeneous skills gap in low-skilled occupations

Within firm, low carbon jobs require more skills

	13-1 - Business Operations Specialists	17-1 - Architects, Surveyors, and Cartographers	17-2 - Engineers	17-3 - Engineering and Mapping Technicians
Low-carb. job	1.545***	3.704***	2.692***	3.178***
	(0.128)	(0.301)	(0.148)	(0.225)
Firm FEs	Yes	Yes	Yes	Yes
R^2	0.32	0.53	0.29	0.41
Observations	5,309,742	144,272	2,433,461	1,167,420

	19-2 - Physical Scientists	47 - Construction and Extraction	49 - Installation, Maintenance, and Repair	53 - Transportation and Material Moving
Low-carb. job	2.377***	2.995***	3.140***	0.737***
	(0.215)	(0.226)	(0.418)	(0.100)
Firm FEs	Yes	Yes	Yes	Yes
R^2	0.43	0.54	0.47	0.56
Observations	234,026	1,049,900	4,154,606	7,853,633

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

Specialization vs diversification by occupation

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

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

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

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

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

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

n is the total number of ads in the sample

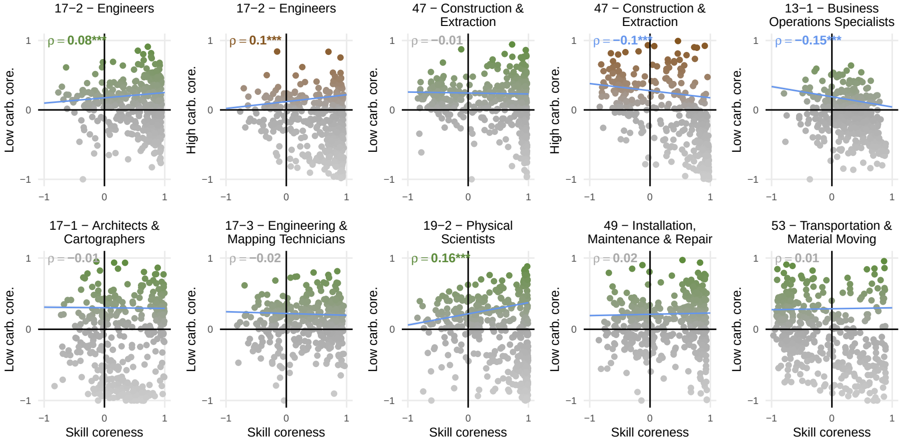
$n_s^{c,SOC}$ is the number of low (resp. high) carbon ads requiring skill s in occupational group SOC

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

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

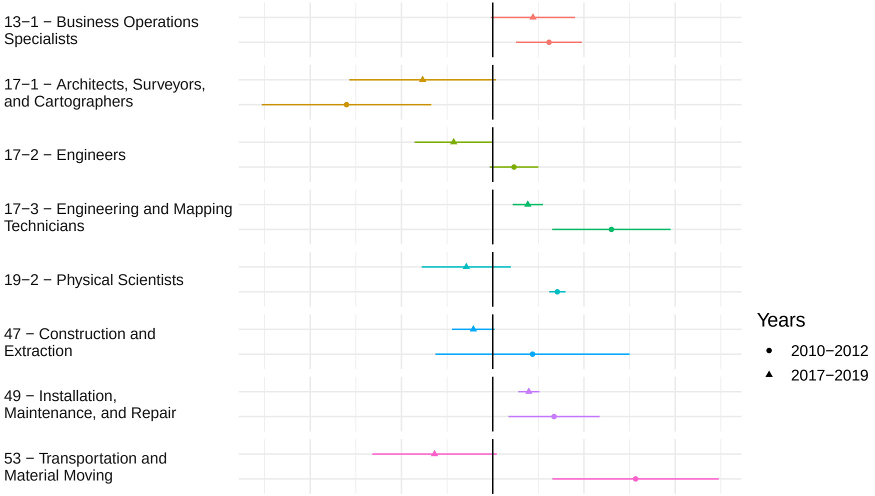
n^{SOC} is the number of ads in occupational group SOC

Specialization vs diversification by occupation



Specialization vs diversification by occupation

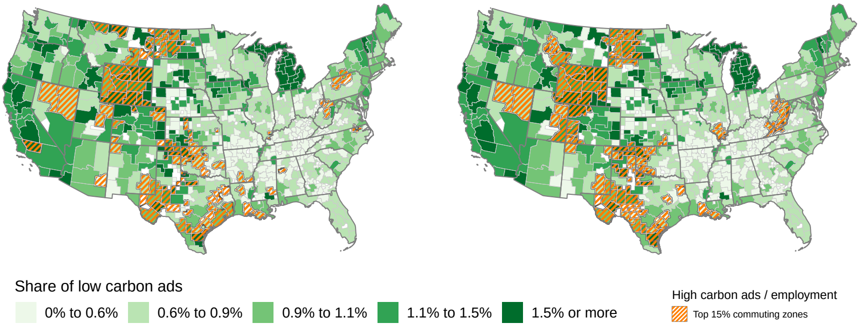
The green wage premium has vanished over the decade



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

Low carbon ads vs high carbon vacancies

Low carbon ads vs high carbon 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**

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