Building Skills for the Low-Carbon Transition: evidence from job ads data

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Abstract

The transition to a carbon-neutral economy involves a substantial growth and reallocation of employment in so-called green sectors, such as energy-efficient building, electric mobility and clean energy. Retraining the workforce is a key, but still under-explored, aspect of such transition. Using a large dataset of nearly 200 million job ads published in the U.S. over the past decade, we examine the skill requirements of green job ads in very specific occupations. Our result underscores highly heterogeneous patterns across occupations in terms of the set of skills needed in low-carbon activities. While the skill gaps between green and non-green job ads are large also within the same occupation, we do not find systematic evidence of a wage premium for green skills.

Keywords: green skills, green jobs, low carbon transition, employment, skills demand, job ads

JEL codes: E24, J62, Q58

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1 Introduction

Green deal plans are seen as a promising strategy to reabsorb the jobs lost during the pandemic, while tackling the climate crisis. This strategy will entail mass industrial restructuring and labour reallocation through a contraction of carbon intensive jobs and expansion of new, green jobs e.g. renewable energy, energy efficiency, public transport and smart mobility. The effectiveness of green stimulus plans depends on the reallocation costs required to move a large fraction of the workforce to sectors involved in the low-carbon transition. Popp et al. (2020) show that the green fiscal push of the American Recovery and Reinvestment Act was twice more effective in communities with the right green skills relative to the average communities. Labour research suggests that the costs of job-to-job transitions are proportional to the similarity of the skill sets required in expanding and contracting occupations (e.g. Gathmann and Schönberg, 2010). The transition to a low-carbon economy should be no exception to this pattern, but research on the skill requirement of clean technologies is still at its infancy compared to the voluminous literature on information and communication technologies and robotics (e.g. Autor et al., 2003; Acemoglu and Autor, 2011).

This paper analyses detailed job vacancy descriptions to start characterizing the skills and labour market dynamics that will gradually emerge as the low-carbon transition takes off. We made use of Burning Glass Technologies (hereafter, BG) data covering the near-universe of online job ads posted in the US between 2010 and 2018. The fine-grained nature of such data allows us to contribute to the literature of green labour markets in several ways, circumventing well-known data and conceptual limitations of previous analyses (Consoli et al., 2016; Vona et al., 2018; Bowen et al., 2018; Vona et al., 2019).

Above all, there is no clear agreement on how to define what a "green" as there are multiple environmental problems and similar goods can be produced with different ecological footprints. The richness of the BG data allows us to identify job ads that are relevant for low-carbon technologies, thereby inferring the specific skill requirement for these technologies. By restricting the perimeter of our analysis, we can make stronger and more specific claims that can be used by both policy makers to design interventions to increase the supply key low-carbon skills (OECD and European Centre for the Development of Vocational Training, 2014) and modelers to calibrate reallocation costs in climate models (Hafstead and Williams III, 2018).

Second, the detailed task-based analysis of Vona et al. (2019) reveals that traditional occupation classifications, even when very detailed as for the US case, stack together green and non-green job titles. To partially circumvent this problem in the Occupational Information Network (O*NET) dataset, Vona et al. (2019) use the share of green task over total task to measure occupational greenness at 6-digit SOC level. While such measure of greenness is suitable to reweigh employment statistics in order to estimate the share of green employment, it does not capture within occupation differences for occupations that can be either green or non-green, i.e. electric engineers and construction workers. This is a crucial issue because it is reasonable to assume that workers are more likely to transition towards green jobs within the same occupational groups. Taking advantage of the high density of green job ads in particular occupations, we are able to explore the skill and wage differences between green and non-green (or brown) job ads in narrowly defined occupational groups.

Finally, we track the evolution of the skill requirement of low-carbon job vacancies compared to similar job vacancies. Because new and emerging technologies, such as clean ones, are rapidly improving, we expect to observed a race between technological change and the set of skills that complement the use of these technologies (Goldin and Katz, 2009; Krusell et al., 2000). We establish a benchmark by comparing the evolution of the skill requirement of clean-energy jobs with that of similar STEM jobs, whose skill sets are known to be rapidly changing. Accounting for these dynamics is important to understand which educational and retraining policies are needed to match the skill requirements of the low-carbon economy.

The remaining of the paper is organized as follows. Section 2 describes the data and the bag of words used to identify jobs vacancies for the low-carbon transition. We show that low-carbon job vacancies are posted in a few broad occupational groups, especially scientists, engineers, construction and maintenance workers. Section 3 extends the methodology proposed by (Vona et al., 2018) to identify the set of skills that are important for the low-carbon transition, allowing green skills to vary across occupations. We also analyse the extent to which the set of low-carbon skills is stable over time (within narrowly defined occupations) and propose an indicator to disentangle if low-carbon skills are part of the core set of skills of an occupation or increase skill diversification. Section 4 tackles the issue of skill gaps in two ways. First, we compute indexes of skill similarities across groups based on our green skill constructs. Second, after providing new evidence on green wage premia, we let the data to reveal the existence of potential skill mismatches by estimating returns to low-carbon skills in wage regressions. Section 5 concludes and discusses the policy implications of our work.

2 Data and descriptives

2.1 Burning Glass Data on Job Ads

The main data source for this project is the large dataset of job ads collected by Burning Glass Technologies (hereafter, BG), a company providing labour market data and analytics to companies, universities and researchers. On a daily basis, BG examines over 40,000 online job search sites and company websites. For each job ad, information is extracted from the open text of ads and coded into a systematic form. Clearly, a posted job ad is not equivalent to a job created, but it is a good proxy of the demand side of the labour market.

The variables collected include skill requirements, company name, location, occupational group (SOC 6-digit), industrial sector, educational and professional experience requirements, and wage. Skill requirements, are extracted based on the prevalence of key words and phrases. The database codes and regularises over 16,000 skill categories. These individual skills are further grouped into two additional hierarchical layers: 659 "skill clusters" and 29 "skill families". Of the 16,000 skills, 9000 skills are uncategorised, and represent around 33% of skills appearing in ads. Each job ad can thus be represented as a vector of binary skill dummies, which indicates whether the job posted would need or not a particular skill, such as quantitative analysis or manual dexterity.

Our dataset covers more than 196 million ads. This data has been used in the recent literature to move beyond the limitations of analysis at the occupation level, by Hershbein and Kahn (2018) and Deming and Kahn (2018) among others. By capturing variation in demand for skills across jobs within narrowly defined occupation categories, it has helped to explain for example wage inequality across firms and labour markets (Deming and Kahn, 2018).

2.2 Data characteristics

As reported in the literature (Deming and Kahn, 2018), BG data tends to over-represent job ads in high-skill professions, such as managers and computer scientists. This reflects the high use of informal channels to recruit low-skilled workers, especially in the service sector. Figure 1 illustrates this issue, by comparing the share of the job ads in a particular 2-digit SOC occupation with the employment share of that occupation in the official Bureau of Labor Statistics (BLS henceforth). For instance, 20% of BG job ads are for computer and mathematics occupations (SOC-15), which represents less than 5% of the total workforce. For this reason, we reweigh our data for BLS employment when aggregation is an issue.

A second problematic feature is the natural counterpart of the richness of BG data. There is a huge variation in the length of the skill vector for each job ad. To illustrate, a job ad can demand from just two skills in the bottom quintile to above 15 in the top quintile. Looking at specific occupations, the length of the job ad exhibits similar degree patterns. This variation can stem from a genuine difference in job complexity (i.e., job ads in high-skill occupations are longer), but reflect a different style of advertising or measurement error. We tackle this issue in our procedure to identify green skills.

Finally, the data collection increases over time. As a result, the average number of job ads collected doubled between the first and the last year of our sample. We take care of this particular feature of the data in what follows.

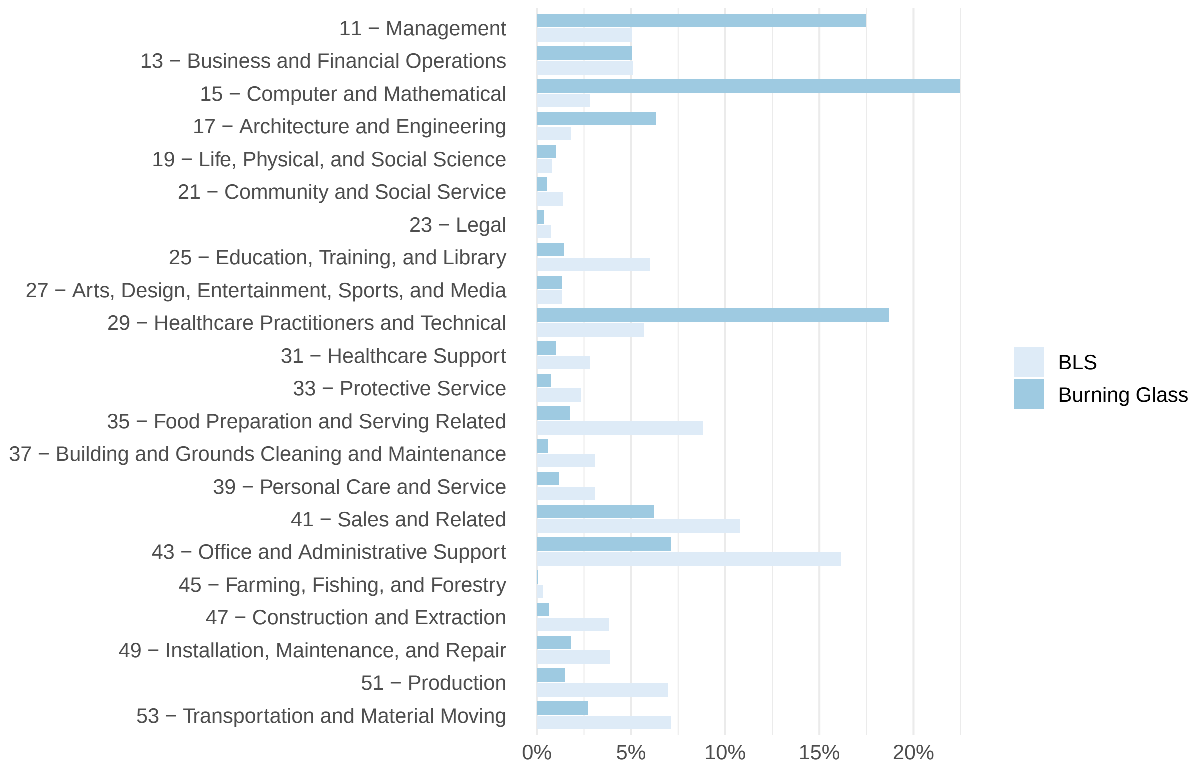


Figure 1: Job ads vs BLS employment by SOC 2-digits occupation (2010-2019)

2.3 Defining green job ads

We adapt the procedure of the seminal paper of Vona et al. (2018). First, we define a set of sub-set of skills as “green”. Job ads that contains at least one green identifier are defined a green, where in this project we focus on low-carbon job vacancies. We keep the label green job ad for simplicity. Second, because we are interested in which general skills appear more frequently in a green job ad, we compare the skill vector of green and non-green job ads along several dimensions.

We describe here the first step of this procedure. While the O*NET database used by Vona et al. (2018) flags certain tasks as green, thus providing a natural green job identifier, BG data do not contain a clear green identifier. However, among the 28 “skill families” (the most aggregated group), there are two that are clearly related to the green economy. First, the skill family “environment” includes skill clusters such as “restoration” and “air quality”. This broad family contains both climate-related job ads and job vacancies posted to solve other environmental problems. Second, the skill family “energy and utility” contains skill clusters such as “wind energy” and “energy efficiency”. In this case, each job ad is attached to a specific energy technology, thus identification of clean-energy job ads is straightforward. Beyond these two families, other families can contain candidates green identifiers. For instance, Electric Car Industry Knowledge is contained in the family "industry knowledge", while Energy Efficient Home Improvement is included in the family "not attributed". In general, job ads in green construction and electric mobility are more spread across different families.

The structure of BG data requires a process of disambiguation to end up with a reliable list of job vacancies for the low-carbon transition. We proceed as follow (details are in the Appendix). We first select a list of low-carbon keywords that take stock from existing classifications of green products and technologies.[1]. Then, we use this conservative set of keywords to identify low-carbon skills among the 16,000 possible skills. To validate our measure, we extract another list of keywords from the O*NET green task statement data file, exclude the keywords that are related to other environmental problems (e.g. water) and repeat steps 1 and 2. We end up with two lists of low-carbon green identifier that are quite similar, which reassures us on the credibility of our final list. We employ a similar procedure to identify a set of identifier from brown job ads, namely job ad in fossil-fuel related activities such as mining, coal energy and extraction.

2.4 Descriptive patterns

Figure 2 presents the share of green job ads in our dataset, weighted by total employement by SOC at the 6-digit level as reported by the U.S. Bureau of Labor Statistics. Green job vacancies represent a very small share of the entire population of job advertisement. This proportion has been quite stable over the past decade, oscillating between 0.6% and 0.8%.

Green job ads are concentrated in four main occupation groups (see Figure 3):

- Architecture and Engineering
- Life, Physical and Social Science

[1] A part from the obvious cases of wind and solar, we include energy efficiency (LED, design, insulation, waterproofing, appliances, etc., carbon management and markets, bicycles, trams and rail. The full list is in the Appendix

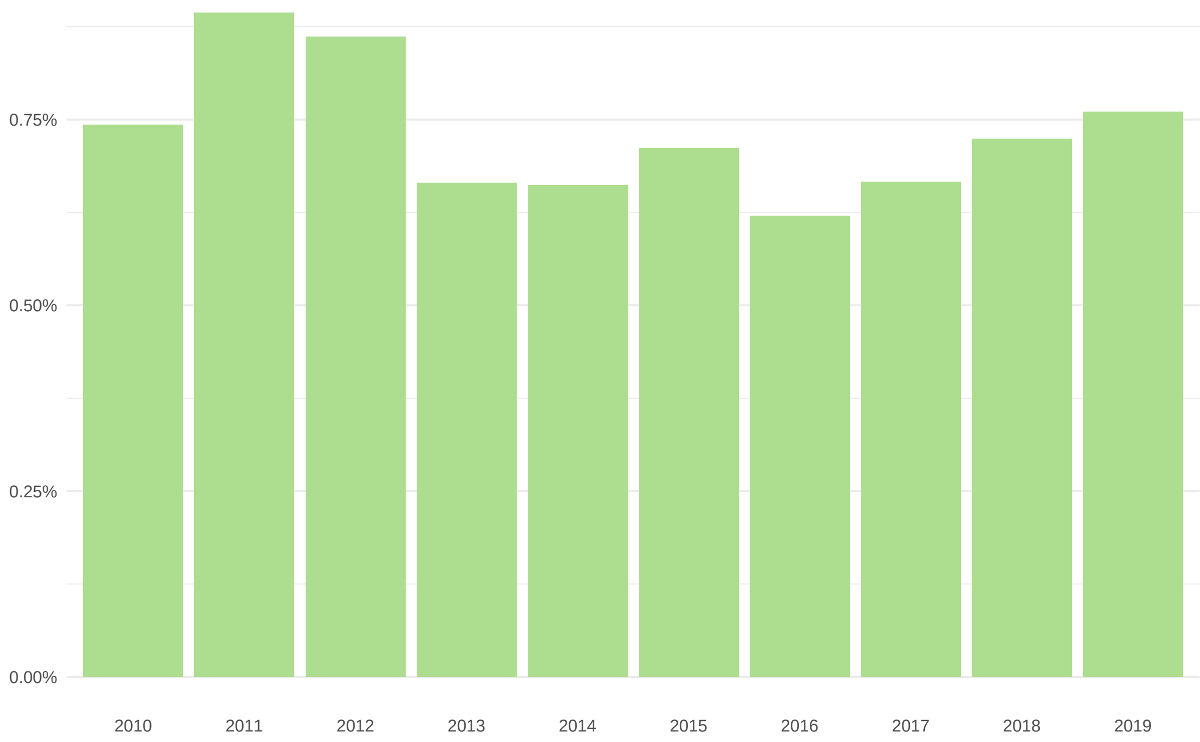


Figure 2: Share of green ads over time (2010-2019)

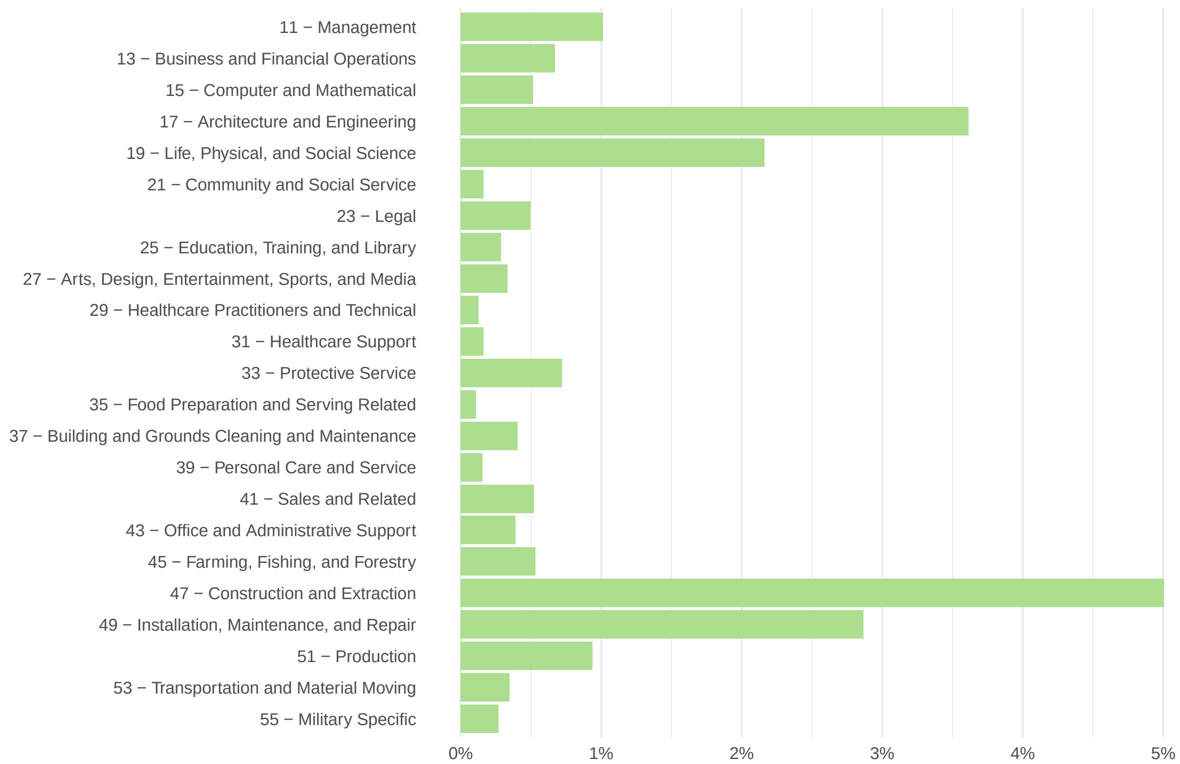


Figure 3: Share of green ads by SOC major group (2010-2019)

- Construction and Extraction
- Installation, Maintenance and Repair

3 The skill content of the low-carbon transition

3.1 Selecting low-carbon skills

- Skills vectors are **grouped by skill clusters and families**
- We then compare green ads vs neither green nor brown ads
  - **within a 3-digits SOC group**
  - **controlling for skill vector length**
- For each SOC-3 group, we estimate the following **probit**:

$$P[\text{skill } s \in \text{ad } i] = \beta_s^{SOC3}\, green_i + S_i + S_i^2 + S_i^3 + \alpha_t + \varepsilon_i \tag{1}$$

- β_s^{SOC3} measures how much the presence of skill s predicts that an ad for a job in SOC3 is green
- This approach can be applied on **both** skill **families** and **clusters**
- We further introduce two measures of skill **relevance** to a given occupation and the greenness of its job ads
- **Skill *coreness*** of skill s in occupation group $SOC3$

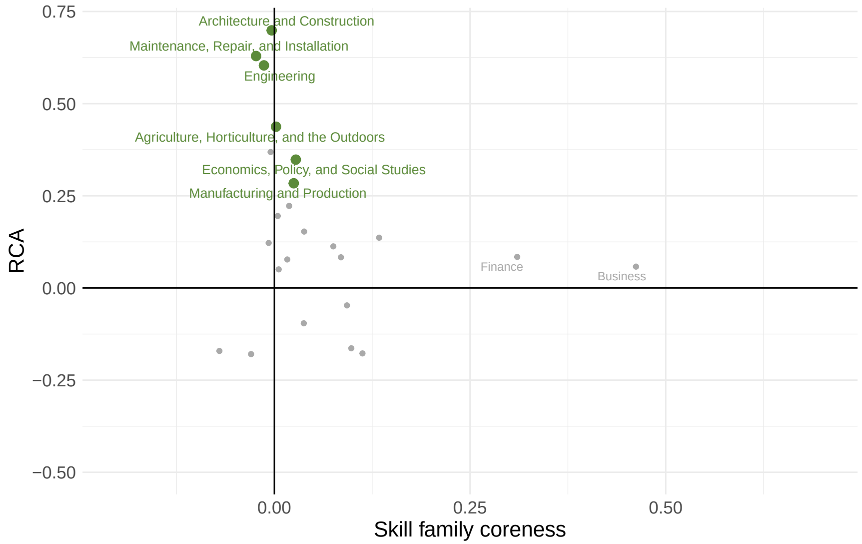
$$c_s^{SOC3} = \frac{n_s^{SOC3}}{n^{SOC3}} - \frac{n_s}{n} \tag{2}$$

  - Measures how **characteristic** the presence of skill s is of $SOC3$ jobs
- **Relative Comparative Advantage** (RCA)

$$RCA_s^{SOC3} = \frac{1 - rca_s^{SOC3}}{1 + rca_s^{SOC3}}, \quad rca_s^{SOC3} = \frac{n_s^{SOC3,g}/n^{SOC3,g}}{n_s^{SOC3}/n^{SOC3}} \tag{3}$$

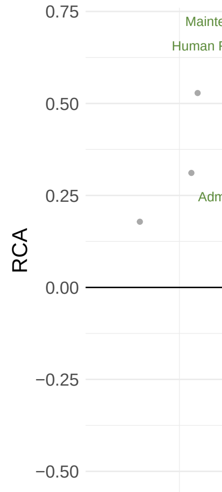
  - Measures how **prevalent** skill s is in **green** $SOC3$ job ads
- **Criteria to select green-related skills**

$$\beta_s^{SOC3} > 0, \quad p < 0.05, \quad RCA_s^{SOC3} > 0 \tag{4}$$



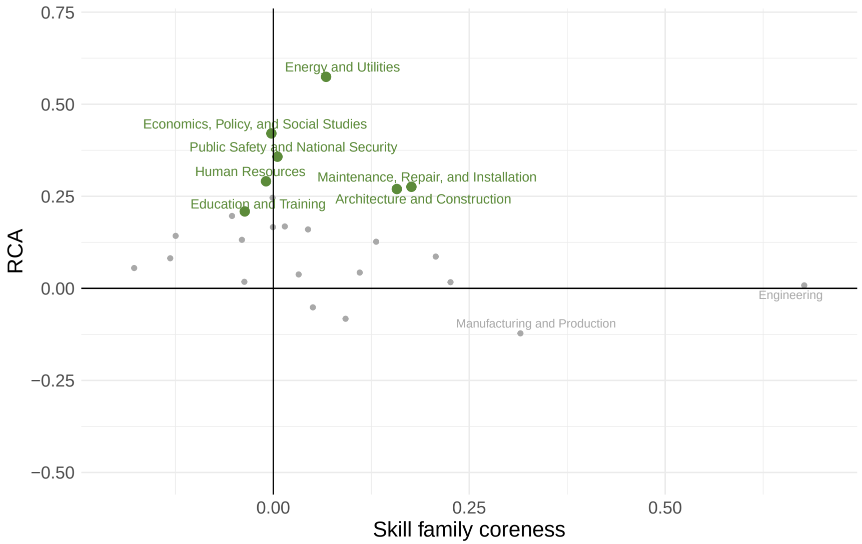
- Top Executives.pdf

(a) 11-1 Top Executives



- Architects, Surveyors, and Cartographers.pdf

(b) 17-1 Architects, Surveyors, and



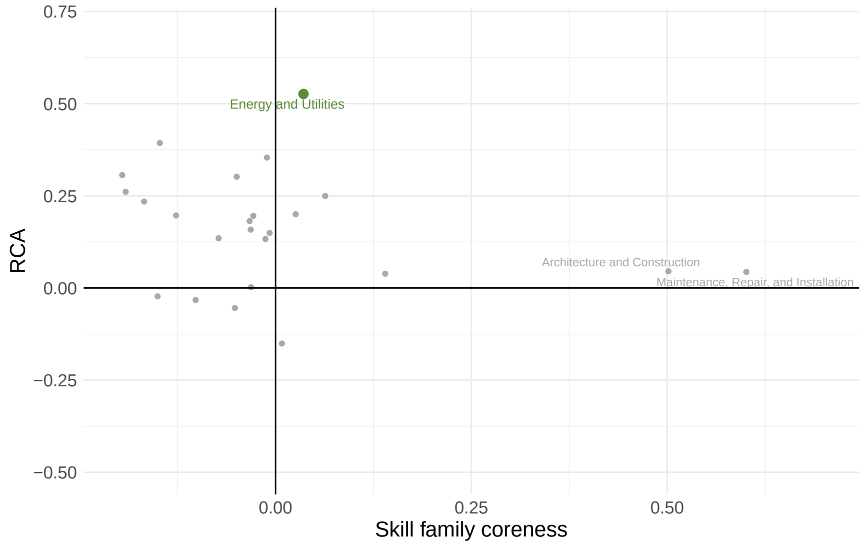
- Engineers.pdf

(c) 17-2 Engineers

- Drafters, Engineering Technicians, and Mapping Technicians.pdf

(d) 17-3 Drafters, Engineering Technici

Figure 4: Green skill families in high-skilled occupations

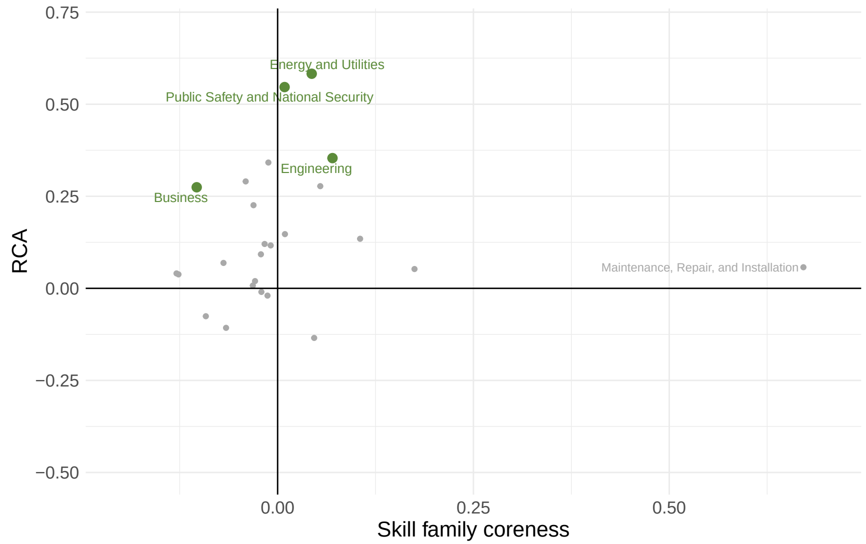


- Construction Trades Workers.pdf

(a) 47-2 - Construction Trades Workers

- Vehicle and Mobile Equipment Mechanics, Insta

(b) 49-3 - Vehicl



- Other Installation, Maintenance, and Repair Occupations.pdf

(c) 49-9 - Other Installation, Maintenance, and Repair Occupations

- Metal Workers and

Figure 5: Green skill families in low-skilled occupations

3.2 Heterogeneity across occupations

- Figures 4 and 5 display green skills identified in a selection high-skilled and low-skilled occupations respectively
- They present a range of green skills configuration, along two dimensions:
  - **diversification**: an occupation's green skills are not predominantly found among its core skills (*e.g.* 11-1, Top Executives)
  - **specialisation**: an occupation's green skills are found among its core skills (*e.g.* 49-3, Vehicle Mechanics)
  - Most occupations display a mix of both (*e.g.* 17-2, Engineers)

3.3 Within occupation dynamics

- Evolution of green skill over time, including within-occupation changes. To be added.

4 Evidence on skill gaps

4.1 Skill distances

- Building on Gathmann & Schönberg (2010), we use the following generalization in n-dimension:

$$proximity_{g,ng} = \frac{\sum_s \frac{n_{g,s}}{n_g} \cdot \frac{n_{ng,s}}{n_{ng}}}{\left[\left(\sum_s \frac{n_{g,s}^2}{n_g^2} \right) \cdot \left(\sum_s \frac{n_{ng,s}^2}{n_{ng}^2} \right) \right]^{\frac{1}{2}}} \tag{5}$$

- The **proximity** between two variants is the (cosine of the) **angular distance between the vectors of skills prevalence in each variant**
- This proximity can be calculated on skill **families** or **clusters**
- It is harder to switch to a green job when coming from a brown occupation (see Figure 6)

4.2 Wage regressions

- If green skills are in short supply we expect them to command a **wage premium**

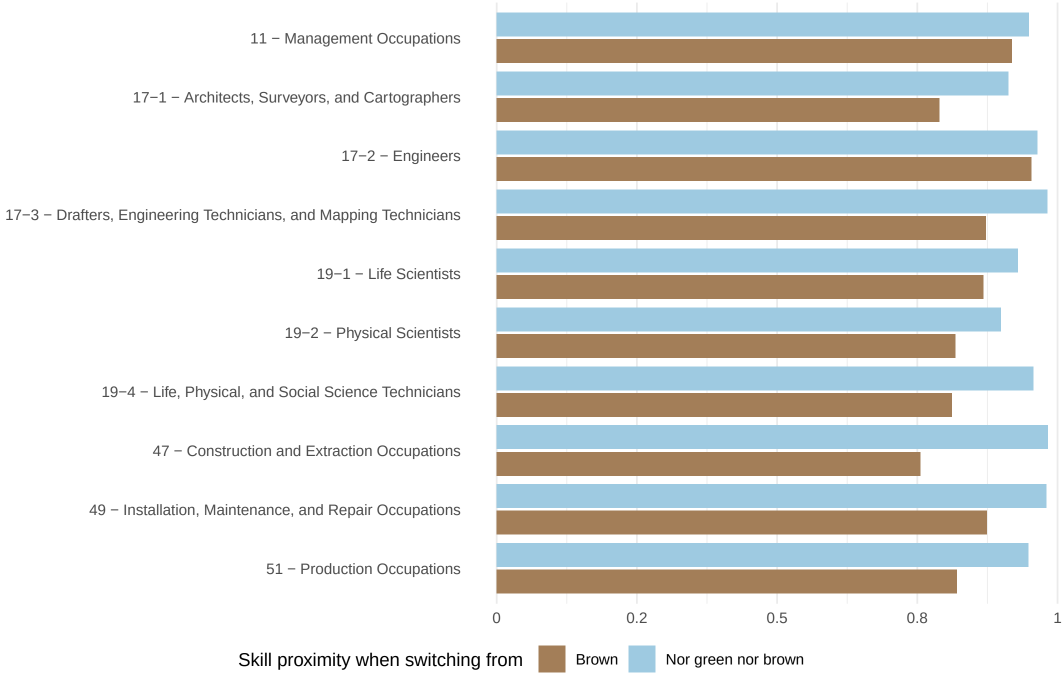


Figure 6: Skill proximity to green jobs at the skill family level

- **Salary** data is available for **20% of the job ads** in our occupations of interest
- For each occupation group, we estimate the following model:

$$\log(w_i) = \sum_{s=1}^{S_i} \Big(\beta_s^{SOC3}\, \mathbb{1}\{s \in i\} + \boldsymbol{\beta}_{\mathbf{s,g}}^{\mathbf{SOC3}}\, \mathbb{1}\{s \in i\} \times green_i + f(edu_i) + f(S_i) + \varepsilon_i \Big)$$

- $\beta_{s,g}^{SOC3} > 0$ tests for the existence of a wage premium for skill s in green ads
- We do not find evidence of systematic wage premia for green skills, neither in high-skill (*e.g.* Engineers, see Figure 7) nor low-skill (*e.g.* Construction Workers, see Figure 8) occupations.

- 17-2.pdf

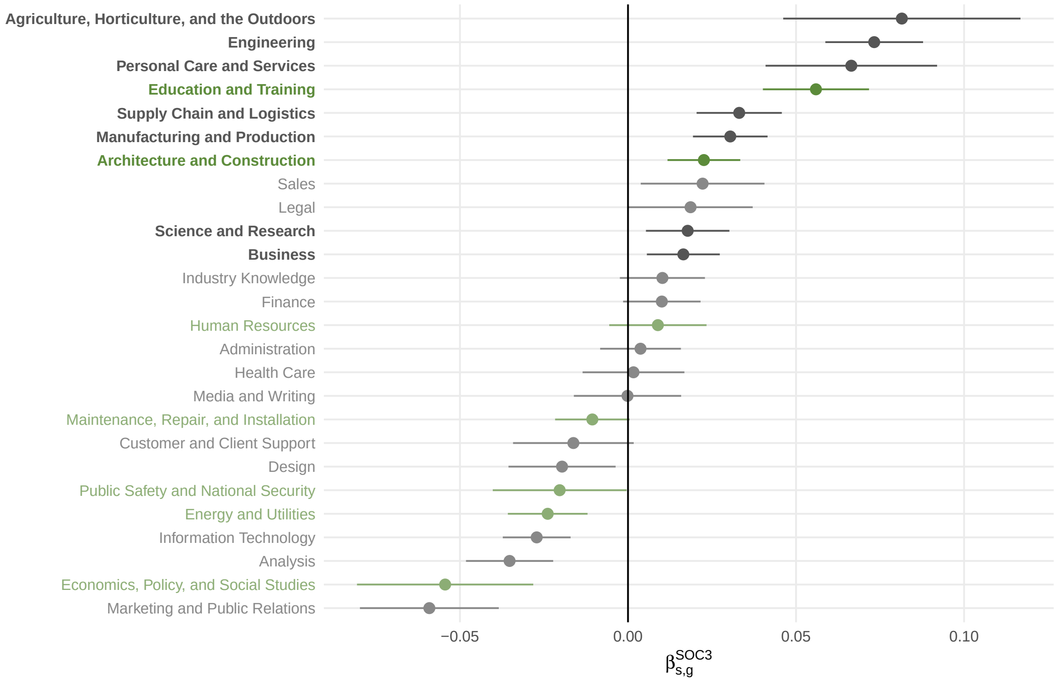


Figure 7: Wage premium by skill family: Engineers (SOC 17-2)

- 47-2.pdf

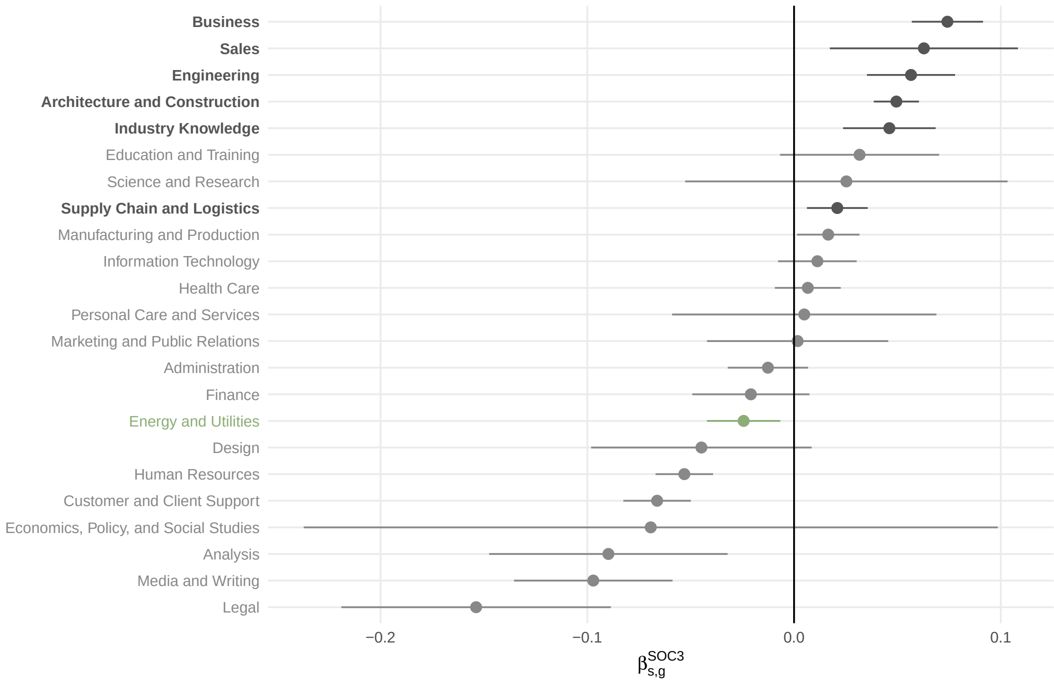


Figure 8: Wage premium by skill family: Construction Trades Workers (SOC 47-2)

5 Conclusion

To be added.

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Online supporting material

Contents

Appendix A Descriptive statistics

A.1 BG data

Appendix B Skills cluster level analysis

B.1 Methodology

B.2 Preliminary results