# Understanding green jobs and skills through online job advertisements

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# Context

- Green jobs and skills are essential for transitioning to an environmentally sustainable economy and achieving climate neutrality.
- Understanding the characteristics of green jobs is crucial for developing informed policies that mitigate the workforce impact of this structural transformation (Causa et al., 2024; Vandeplas et al., 2022).
- What do we know about green jobs?
  - Higher levels of education, experience, and on-the-job training.
  - Less routinized, requiring analytical and interpersonal skills (Consoli et al., 2016).
  - Higher job quality and wages (Bowen et al., 2018; Valero et al., 2021).
- Prominent definition: Green jobs are defined by task content Vona et al., 2019$\rightarrow$ Gradient of **"greenness"** based on the share of green tasks within occupations. Uses O*NET data, extended to ISCO-08 (4-digit level) by Scholl et al., 2023.

# Complementing tasks analysis with skills analysis

**WHAT?** → **TASK**: specific work **activities** that can be unique for each occupation. →

**Green occupations (O*NET – ISCO-08):**
Greenness as measure of relevance of green tasks within an occupation.

- Invariant across sectors and production techniques

**Examples:** *Analyze green product marketing or sales trends to forecast future conditions; Communicate geothermal plant conditions to employees.*

**HOW?** → **SKILLS:** the use of methods or instruments in a particular setting and in relation to defined tasks. →

**Green Online Job Advertisements (ESCO-Cedefop)** to identify green skill requirements and explore within ISCO-08 variation.

- We can study variation across sectors, countries, …

**Examples:** *animal welfare, green computing, pollution law*

# Research Goals

Using green skills and OJA data, we conduct an analysis on **26 European countries and the UK (2019-2023)**, focusing on these questions:

**What are the main characteristics of green OJAs compared to non-green OJAs in terms of education, experience, and wages?**

**What role do green skills play in traditionally non-green (brown) occupations?**

**How similar or distinct are green OJAs compared to non-green OJAs in terms of skillsets?**

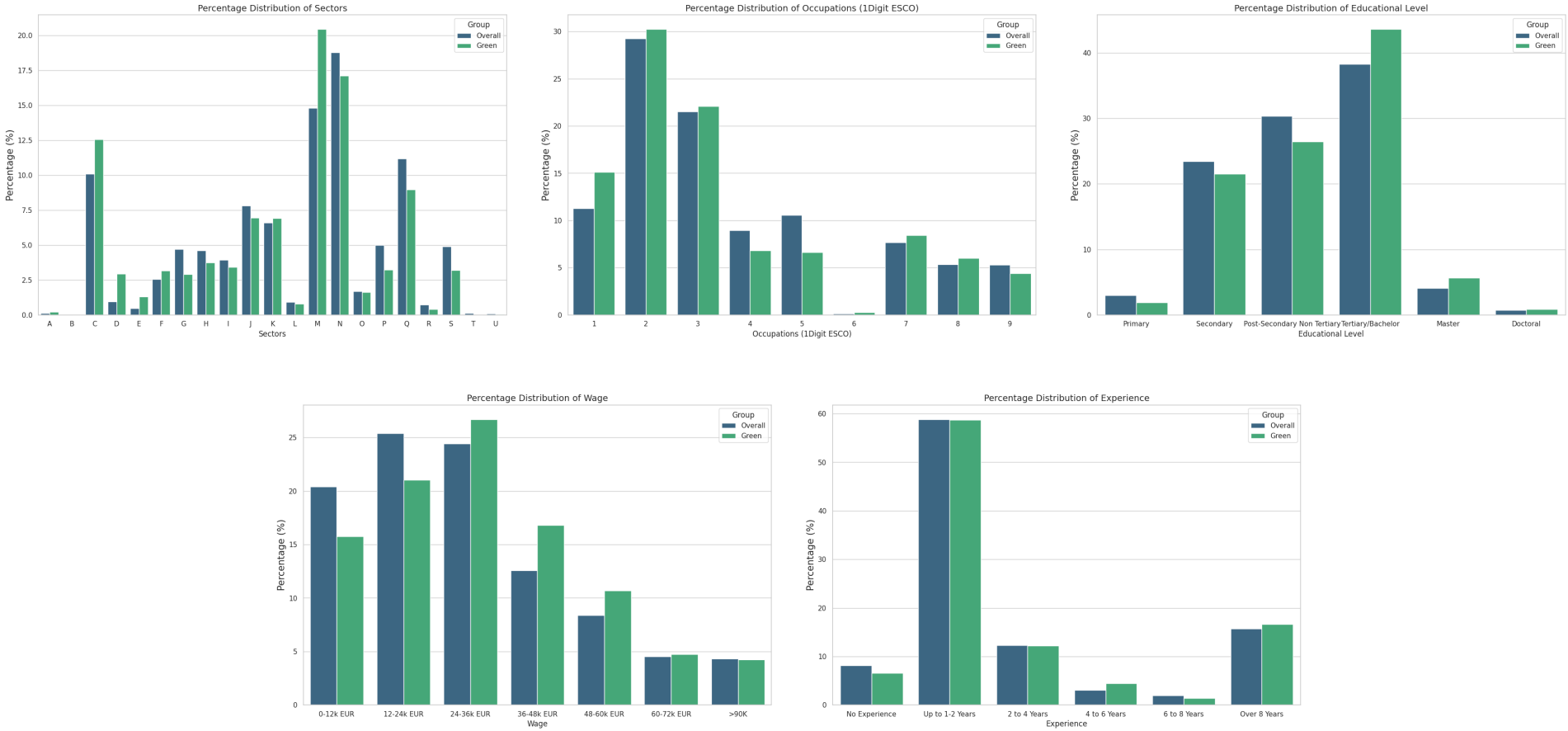
# Data

- Source: **Eurostat's Web Intelligence Hub (WIH)** (2019–2023).
- $\sim$ 29 million OJAs from 26 EU countries and the UK which have jointly valid values for **country, date, ISCO-08 occupation, wage, education, experience, NACE macrosector**.
- Green job identification:
  - An OJA is green if it includes at least one green skill (they represent $\sim$ 5% of our population) .
  - Green skills defined using ESCO and Cedefop classifications[1] .
- Focus on heterogeneity within ISCO-08 occupations.
- Data selection: Validation of Occupation-Skill Relations; exclusion of ESCO knowledge and language concepts.

[1] ESCO and Cedefop Green Taxonomy

# Findings: Descriptive Evidence

Figure: Percentage distribution of Green and not-Green OJA for all dataset variables




Note: authors' calculations on WIH-OJA data

# Findings: Profiling of Green OJA

Following Consoli et al. (2016) we estimate a OLS-FE equation to capture the characteristics of green OJA compared to non-green ones (353 occupations ISCO-08 4th digit).

$$y_{i,c,s,t} = \beta green_{i,c,s,t} + \Gamma FE_{i,c,s,t} + \epsilon_{i,c,s,t} \quad (1)$$

| | (1) Education | (2) Experience | (3) Wage |
|---|---|---|---|
| Green OJA | 0.0466*** | -0.0166*** | 0.169*** |
| | (0.000987) | (0.00191) | (0.00253) |
| Education | | 0.0174*** | 0.0701*** |
| | | (0.000356) | (0.000499) |
| Experience | | | 0.0857*** |
| | | | (0.000257) |
| Constant | 4.282*** | 3.326*** | 4.789*** |
| | (0.000212) | (0.00158) | (0.00236) |
| Sector FE | ✓ | ✓ | ✓ |
| Isco FE | ✓ | ✓ | ✓ |
| Isco*Sector FE | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ |
| Observations | 29236392 | 29236392 | 29236392 |
| $R^2$ | 0.281 | 0.068 | 0.152 |

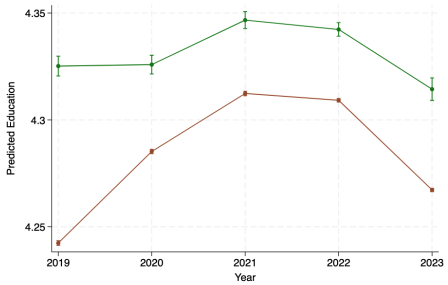
Source: Authors' calculation on WIH-OJA data.
*Notes:* Each observation consists of an OJA. OLS regression using education, wage and experience as the dependent variable. Robust standard errors in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05.

- *green* is a dummy identifying green OJA, $\Gamma_{i,C,S,t}$ is a matrix of dummy variables for *i* occupation, *C* country, *S* sector and *t* year.
- **Findings:** Green OJA are required higher levels of education, shorter experience, and are offered higher wages
- Results are in line with Consoli et al., 2016.

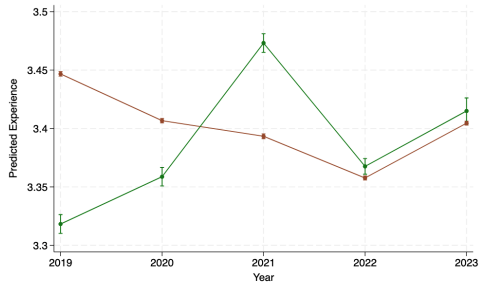
# Findings: Profiling of Green OJA

Adding time interaction to the green dummy, we observe trends over time

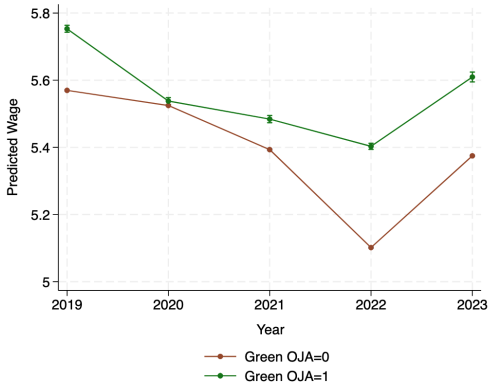
$$y_{i,c,s,t} = \beta \, \text{green}_{i,c,s,t} I_t + I_{i,c,s} \Delta + \epsilon_{i,c,s,t} \tag{2}$$




(a) Years and Education




(b) Years and Experience




(c) Years and Wage

Figure: Interaction effects: Time variable with Green OJA Dummy

# Findings: Green skills and brown occupations

We use Scholl et al., 2023 Greenness indicator - based on Vona et al., 2019 - to study its interaction with Green OJA.

| | (1) Education | (2) Experience | (3) Wage |
|---|---|---|---|
| Green OJA | 0.0359*** | -0.0478*** | 0.148*** |
| | (0.00165) | (0.00326) | (0.00418) |
| Brown occupation | -0.0844*** | -0.0539*** | -0.0351*** |
| | (0.000895) | (0.00180) | (0.00237) |
| Green OJA × Brown occupation | 0.00420* | 0.0554*** | 0.0383*** |
| | (0.00205) | (0.00400) | (0.00522) |
| education | | 0.0178*** | 0.0709*** |
| | | (0.000357) | (0.000498) |
| experience | | | 0.0872*** |
| | | | (0.000257) |
| Constant | 4.346*** | 3.365*** | 4.807*** |
| | (0.000701) | (0.00209) | (0.00297) |
| Isco FE (Digit 3) | ✓ | ✓ | ✓ |
| Sector FE | ✓ | ✓ | ✓ |
| Isco*Sector FE | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ |
| Observations | 29233060 | 29233060 | 29233060 |
| $R^2$ | 0.279 | 0.070 | 0.158 |

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an OJA. We define Brown occupations as the ones with no assigned *greenness* levels in the OECD classification. OLS regression using education, experience, and wage as the dependent variable. Robust standard errors in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05.

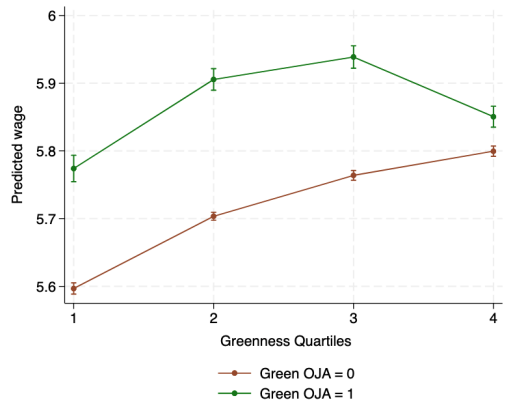
- OLS-FE estimated at the OJA level, adding an interaction between a green occupation dummy with the green OJA dummy.
- **Findings:** green skills have a positive correlation with education and experience requirements as well as wage for non-green occupations

# Findings: Green skills and green occupations

| | (1) Education | (2) Experience | (3) Wage |
|---|---|---|---|
| Green OJA | 0.0572*** | -0.120*** | 0.177*** |
| | (0.00322) | (0.00690) | (0.00950) |
| Greenness Q2 | 0.172*** | 0.277*** | 0.107*** |
| | (0.00210) | (0.00436) | (0.00571) |
| Greenness Q3 | 0.199*** | 0.313*** | 0.167*** |
| | (0.00249) | (0.00471) | (0.00642) |
| Greenness Q4 | 0.267*** | 0.229*** | 0.203*** |
| | (0.00260) | (0.00528) | (0.00701) |
| Green OJA × Greenness Q2 | -0.0650*** | 0.0876*** | 0.0248* |
| | (0.00436) | (0.00934) | (0.0124) |
| Green OJA × Greenness Q3 | -0.0376*** | 0.0294** | -0.00239 |
| | (0.00492) | (0.00952) | (0.0127) |
| Green OJA × Greenness Q4 | 0.00939* | 0.0936*** | -0.126*** |
| | (0.00443) | (0.00924) | (0.0122) |
| education | | 0.0540*** | 0.0552*** |
| | | (0.000777) | (0.00102) |
| experience | | | 0.110*** |
| | | | (0.000491) |
| Constant | 4.315*** | 3.160*** | 4.956*** |
| | (0.00160) | (0.00462) | (0.00631) |
| Isco FE (Digit 3) | ✓ | ✓ | ✓ |
| Sector FE | ✓ | ✓ | ✓ |
| Isco*Sector FE | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ |
| Observations | 7433134 | 7433134 | 7433134 |
| $R^2$ | 0.247 | 0.048 | 0.145 |

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an OJA of a Green Occupation according to the OECD Classification. OLS regression using education, experience, and wage as the dependent variable. Robust standard errors in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05.

- Resticted sample: green occupations only to study heterogeneity across the greenness distribution.
- Findings: higher greenness is associated with **lower contribution of green skills to the wage premium** and **higher education requirements** for green OJA.




Note: authors' calculations on WIH-OJA data

# Skill requirements: non-green skills

Differences between green and non-green OJA skillsets using a Jaccard distance.

| | (1)<br>Jaccard Distance |
|---|---|
| Cognitive skills | 0.0561*** |
| | (0.00239) |
| Social and communication skills | 0.406*** |
| | (0.00890) |
| Digital skills | 0.0687*** |
| | (0.00237) |
| Manual skills | 0.0466*** |
| | (0.00151) |
| Management skills | 0.392*** |
| | (0.00811) |
| Constant | 0.0328*** |
| | (0.00181) |
| Isco FE | ✓ |
| Time FE | ✓ |
| Country FE | ✓ |
| Observations | 8785 |
| $R^2$ | 0.972 |

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an occupation for each observed year and country. OLS regression using Jaccard Distance between green and not green OJA as the dependent variable. Robust standard errors in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05.

$$J_i = 1 - \frac{S_{(i,g)} \cap S_{(i,ng)}}{S_{(i,g)} \cup S_{(i,ng)}}$$

- The Jaccard distance is additive: the overall distance is a linear combination of the Jaccard distance calculated for mutually exclusive and exhaustive groups of skills.
- **Findings**: differences are mainly explained by **social and communication skills and management skills**[a].

[a] We introduce an aggregate coarse classification that distinguishes between Cognitive, Digital, Manual, Management, and Social and Communication skills.

# Skill requirements: specialization

Green skills aside, do green OJA have more distinctive and unique skillsets? Which skill types lead their specialization?

| | (1) RSCA |
|---|---|
| Green OJA | 0.0805*** |
| | (0.00142) |
| Management skills | -0.0426*** |
| | (0.00133) |
| Cognitive skills | 0.0840*** |
| | (0.00194) |
| Digital skills | 0.0930*** |
| | (0.00186) |
| Manual skills | 0.143*** |
| | (0.00208) |
| Green OJA × Management skills | -0.00276 |
| | (0.00210) |
| Green OJA × Cognitive skills | 0.0232*** |
| | (0.00313) |
| Green OJA × Digital skills | -0.0351*** |
| | (0.00293) |
| Green OJA × Manual skills | 0.00753* |
| | (0.00345) |
| Constant | 0.251*** |
| | (0.000878) |
| Isco FE 3Digit | ✓ |
| Time FE | ✓ |
| Country FE | ✓ |
| Observations | 926671 |
| $R^2$ | 0.056 |

Source: Authors' calculation on WIH-OJA data.
Note: Each observation consists of an occupation-skill pair. OLS regression using RSCA measure as the dependent variable. Robust standard errors in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05.

$$rca_{os} = \frac{\frac{sf_{os}}{\sum_{j=1}^{J} sf_{oj}}}{\frac{\sum_{k=1}^{K} sf_{ks}}{\sum_{k=1}^{K}\sum_{j=1}^{J} sf_{kj}}} = \frac{sf_{os}}{\frac{\sum_{k=1}^{K} sf_{ks}}{K}}$$

If the $rca_{os} > 1$, it indicates specialization. However, the $rca_{os}$ is $\in [0, +\infty)$ and lacks symmetry around its neutral value. We use the Symmetric Revealed Comparative Advantage (RSCA) by Laursen, 2015:

$$rsca_{os} = \frac{rca_{os} - 1}{rca_{os} + 1}$$

- Findings: green OJA have distinctive skill sets driven by **cognitive and manual skills**

# Conclusions

- We develop a study of **green jobs identified by green skills (know-how expressed in employment demand). OJA provide granular data** to analyze trends and investigate heterogeneity within occupation ISCO-08.
- We manage to shed light on the role of **green skills in brown occupations** and show that the latter enjoy a wage premium if they are required green skills.
- We observe that t**heir skillsets are more distinctive and specialized in cognitive and manual skills** compared to non-green ones.

$\Longrightarrow$ **Policy implications**: Insights for training, upskilling, and reskilling workforce for green transition.

Thank you!

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# References I


Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018).Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, *72*, 263–275. https://doi.org/10.1016/j.eneco.2018.03.015

Causa, O., Nguyen, M., & Soldani, E. (2024).Lost in the green transition? measurement and stylized facts. *OECD Economics Department Working Papers*, (1796). https://doi.org/10.1787/dce1d5fe-en

Consoli, D., Marin, G., Marzucchi, A., & Vona, F. (2016).Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, *45*(5), 1046–1060. https://doi.org/10.1016/j.respol.2016.02.007

Laursen, K. (2015).Revealed comparative advantage and the alternatives as measures of international specialization. *Eurasian Business Review*, *5*(1), 99–115. https://doi.org/10.1007/s40821-015-0017-1

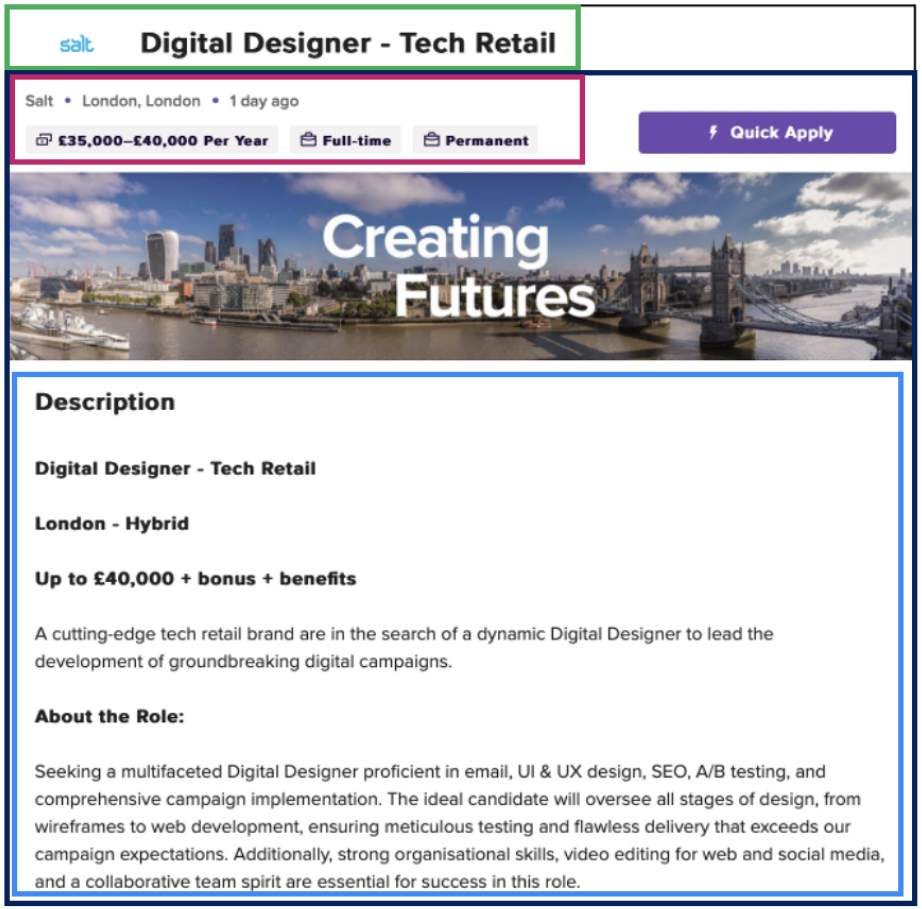
Scholl, N., Turban, S., & Gal, P. N. (2023, May). *The green side of productivity: An international classification of green and brown occupations* (OECD Productivity Working Papers No. 33). OECD Publishing. https://doi.org/10.1787/a363530f-en

Valero, A., Li, J., Muller, S., Riom, C., Nguyen-Tien, V., & Draca, M. (2021). *Are 'green' jobs good jobs? how lessons from the experience to-date can inform labour market transitions of the future*. Grantham Research Institute on Climate Change, the Environment, and Centre for Economic Performance.

Vandeplas, A., Vanyolos, I., Vigani, M., & Vogel, L. (2022, December). *The Possible Implications of the Green Transition for the EU Labour Market* (European Economy - Discussion Papers No. 176). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission. https://ideas.repec.org/p/euf/dispap/176.html

Vona, F., Marin, G., & Consoli, D. (2019).Measures, drivers and effects of green employment: Evidence from us local labor markets, 2006-2014. *Journal of Economic Geography*, *19*(5), 1021–1048. https://doi.org/10.1093/jeg/lby038

# Appendix: What is an OJA?




**Job title** → Occupation ISCO08 IV digit

**Job description** [Structured or unstructured]

→ Requirements classified with standard taxonomies:

- Skills (ESCO Skill pillar)
- Geographical entities (NUTS, down to LAU)
- Economic sectors (NACE)
- Contract type (Perm, Temp, Self-employed)
- Wages (Eurostat classes)
- Education (ISCED 1)
- Experience

32 language specific classifiers for each variable for more than 1,000 sources (400mln OJA).

**All classification pipelines are independent.**

# Appendix: Skills Groups

Figure: Skills Groups

| Groups | ESCO Skill Codes | Description |
|---|---|---|
| Cognitive skills | S2: Information skills, T2: Thinking skills, T1.1: Mastering languages, T1.2: Working with numbers, T6: Life skills and competences | Skills related to problem-solving, information processing, and learning, including language mastery and numerical abilities. |
| Social and communication skills | T4: Social and communication skills, S3: Assisting and caring, S1: Communication collaboration and creativity | Skills referred to the ability to communicate, interact and engage with colleagues, clients, and customers. |
| Digital skills | S5: Working with computers, T1.3: Working with digital devices and applications | Skills that encompass a range of different abil- ities that allow an individual to use ICT tools at different levels. |
| Manual skills | T5: Physical and manual skills and competences, S6: Handling and moving, S7: Constructing, S8: Working with machinery and specialized equipment | Skills related to physical and manual labor, including handling, moving, constructing, and working with machinery. |
| Management skills | S4: Management skills, T3: Self-management skills and competences | Skills including leadership, organization, and decision-making. |