# Skill Demand and Regional Productivity

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*Harnessing web data for next-generation skills intelligence*
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# Introduction

# Motivation

Rapid advancements in technologies, including GPTs, change the way in which products and services are produced and traded, demanding new skills and tasks (Autor et al. 2024)

Firms adapt their skill requirements to integrate these technologies (and increase productivity) (Ciarli et al. 2021) in the context of:

- a yet-unexplained productivity slowdown (Goldin et al. 2024)
- the twin-transition (Nelli et al. 2026)

The availability and diversity of skills within firms significantly impact productivity (Criscuolo et al. 2021): human capital at the core of competitiveness Union of Skills

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# This paper

Theory suggests that regions that update their skills are more productive – higher number of possible combinations. Not clear which types of combinations!

**What is the relationship between a region's skills demand its productivity?**

- Regional skill-spaces – Online Job Advertisements (OJA)
  - **Skill concepts**: skills, knowledge, transversal skills
  - **Skills portfolio characteristics**: coherence, fitness, entropy
  - **Skill types**: green, digital
- Regional Productivity – ARDECO

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# Why skills?

- Jobs consist of bundles of tasks that workers carry out using their skills (Neffke 2019):

Five skills (management, oral comprehension, maths, programming, design) of

$$\text{Manager} = \begin{bmatrix}1\\1\\0\\0\\0\end{bmatrix}, \quad \text{Web designer} = \begin{bmatrix}0\\1\\0\\1\\1\end{bmatrix}, \quad \text{Data analyst} = \begin{bmatrix}0\\1\\1\\1\\0\end{bmatrix}$$

- Skills co-occur and gain value through recombination in **skill spaces**; they cluster together forming socio-cognitive clusters (Alabdulkareem et al. 2018) and their market value depends on its combinations (Stephany and Teutloff 2024)
- Also in production, skills are **recombinatory human capital**: demanded by technologies/processes and raising productivity by enabling new synergies Skill spaces
- Economic complexity principle: The whole knows more because individuals know different

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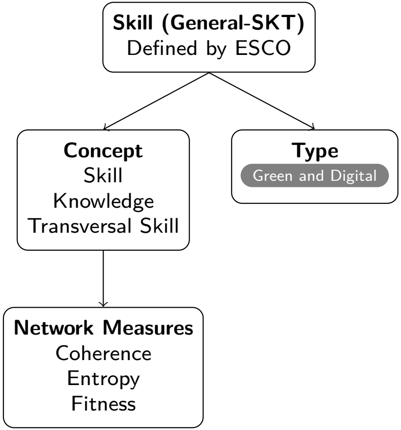
# Methodology

# Data

- Lightcast: ∼130M Online Job Advertisements (OJA) across Austria, Belgium, Switzerland, Germany, Denmark, France, Luxembourg, Netherlands, Norway, Sweden, and UK in the period 2014-2019: skills, region (NUTS3), industry (NACE 2), date, and education requirements.
- Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO): Labour productivity (hours), fixed capital formation
- European Skills, Competences, Qualifications and Occupations (ESCO): Skill hierarchy and types (skills (S), knowledge (K), transversal skills (T)), green and digital skills relevant to the EU labour market.

## Skill Framework Structure




Full method

## ESCO Skill Concepts

To capture demanded skills in as much detail as possible, we use the ESCO skill pillar to distinguish:

- Knowledge (K) – "the outcome of a learning process" (e.g., engineering principles, procedural law)
- Skills (S) – "the ability to apply acquired knowledge; specific method, instrument, or ability used to perform a particular task" (e.g., reading position coordinates, adapting to change)
- Transversal Skills and Competences (T) – "skills that apply to various situations and settings" (e.g., communication, problem-solving)

# Pipeline

1. **Skills classification:** Allocate EU skills from Lightcast labels to the ESCO framework via embedding similarity
2. **Regional specialisation:** Identify skills demanded by regions *more than randomly* using a null model
3. **Skills spaces:** Obtain skills network from the bipartite projection of the specialisation matrix
4. **Skills combinations:** Use skills specialisation and co-occurrence to characterise the bundles of skills demanded by regions in terms of their coherence, complexity, entropy
5. **Twin transition skills:** Identify the share of green and digital skills demanded
6. **Skills demand and productivity:** Measure relationship between skills demand and productivity

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# Empirical model

Two estimation strategies (10 countries, NUTS-3):

**Panel FE (2014-2019):**

$$LP_{r,t+1} = \alpha + \beta \mathbf{SP_{rt}} + \gamma \mathbf{ST_{rt}} + \theta \mathbf{X_{rt}} + \sigma_r + \tau_t + \epsilon_{rt}$$

**Long difference (2019-2014)** (Acemoglu and Restrepo 2019): LP distribution

$$\Delta LP_{r,T-t} = \alpha + \beta \Delta \mathbf{SP_{r,T-t}} + \gamma \Delta \mathbf{ST_{r,T-t}} + \theta \mathbf{X_{r,t}} + \epsilon_r$$

$$\Delta LP_{r,T-t} = \alpha + \beta \mathbf{SP_{r,t_0}} + \gamma \mathbf{ST_{r,t_0}} + \theta \mathbf{X_{r,t_0}} + \epsilon_r$$

$LP$: labour productivity  $SP$: portfolio characteristics (complexity, coherence, entropy)  $ST$: skill types (digital, green)  $X$: controls (time-varying or baseline)  $\sigma_r$: region FE  $\tau_t$: year FE

# Results

# Regional productivity and skill portfolio: Panel regression with FE

| Dep. Variable: LP (log) | (1) All | (2) All | (3) All | (4) S | (5) S | (6) S | (7) K | (8) K | (9) K |
|---|---|---|---|---|---|---|---|---|---|
| L.Coherence (log) | −0.014*** (0.004) | | | −0.014*** (0.003) | | | −0.004 (0.003) | | |
| L.Fitness (log) | | −0.003*** (0.001) | | | −0.004*** (0.001) | | | −0.002*** (0.001) | |
| L.Entropy | | | −0.011*** (0.003) | | | −0.012*** (0.002) | | | −0.004* (0.002) |
| Capital formation (log) | 0.171*** (0.023) | 0.170*** (0.023) | 0.171*** (0.023) | 0.171*** (0.023) | 0.171*** (0.023) | 0.172*** (0.023) | 0.170*** (0.023) | 0.170*** (0.023) | 0.171*** (0.023) |
| Population (log) | 0.233** (0.100) | 0.245** (0.098) | 0.247** (0.100) | 0.229** (0.100) | 0.247** (0.098) | 0.253** (0.099) | 0.246** (0.100) | 0.241** (0.099) | 0.245** (0.099) |
| EU patents (count) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) | 0.001 (0.001) |
| Skill diversity (log) | 0.021*** (0.007) | 0.020*** (0.007) | 0.020*** (0.007) | 0.022*** (0.007) | 0.019*** (0.007) | 0.019*** (0.007) | 0.020*** (0.007) | 0.020*** (0.007) | 0.019*** (0.007) |
| Employment (log) | −0.633*** (0.073) | −0.637*** (0.072) | −0.638*** (0.072) | −0.634*** (0.072) | −0.636*** (0.072) | −0.625*** (0.072) | −0.633*** (0.072) | −0.635*** (0.072) | −0.633*** (0.072) |
| Observations | 3236 | 3236 | 3236 | 3236 | 3236 | 3236 | 3236 | 3236 | 3236 |
| Adj. $R^2$ | 0.993 | 0.993 | 0.993 | 0.993 | 0.993 | 0.993 | 0.993 | 0.993 | 0.993 |
| Within $R^2$ | | | | 0.206 | 0.210 | 0.208 | 0.198 | 0.200 | 0.199 |
| Region FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Skill portfolio scatterplots

# Regional productivity and skill portfolio: Panel regression with FE

| Dep. Variable: LP (log) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| L.Coherence (log) | 0.022** | 0.021 | 0.018 | | | | | | |
| | (0.009) | (0.013) | (0.011) | | | | | | |
| L.Fitness (log) | | | | 0.021*** | 0.007 | 0.008 | | | |
| | | | | (0.005) | (0.006) | (0.006) | | | |
| L.Entropy | | | | | | | 0.004 | 0.014 | 0.016 |
| | | | | | | | (0.009) | (0.011) | (0.011) |
| Capital formation (log) | | | 0.024 | | | 0.024 | | | 0.027 |
| | | | (0.018) | | | (0.018) | | | (0.018) |
| Population (log) | | | 0.408 | | | 0.416 | | | 0.406 |
| | | | (0.283) | | | (0.282) | | | (0.281) |
| EU patents (IHS) | | | −0.002 | | | −0.001 | | | −0.001 |
| | | | (0.003) | | | (0.003) | | | (0.003) |
| Skill diversity (log) | | | −0.018 | | | −0.017 | | | −0.014 |
| | | | (0.023) | | | (0.023) | | | (0.024) |
| Employment (log) | | | −0.723*** | | | −0.727*** | | | −0.728*** |
| | | | (0.068) | | | (0.068) | | | (0.068) |
| Observations | 830 | 830 | 830 | 830 | 830 | 830 | 830 | 830 | 830 |
| Adj. $R^2$ | 0.006 | 0.945 | 0.956 | 0.022 | 0.945 | 0.956 | −0.001 | 0.945 | 0.956 |
| Within $R^2$ | | 0.006 | 0.213 | | 0.003 | 0.212 | | 0.003 | 0.212 |
| Region FE | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Year FE | NO | YES | YES | NO | YES | YES | NO | YES | YES |

# Regional productivity and skill portfolio: Long difference regression

| Dep. Variable: Δ LP (log) | (1) All | (2) All | (3) All | (4) S | (5) S | (6) S | (7) K | (8) K | (9) K |
|---|---|---|---|---|---|---|---|---|---|
| Δ Coherence (log) | −0.015* | | | −0.008 | | | −0.012 | | |
| | (0.009) | | | (0.008) | | | (0.009) | | |
| Δ Fitness (log) | | −0.003* | | | −0.004** | | | −0.003* | |
| | | (0.002) | | | (0.002) | | | (0.002) | |
| Δ Entropy | | | −0.012* | | | −0.010 | | | −0.012* |
| | | | (0.007) | | | (0.006) | | | (0.007) |
| $R^2$ | 0.139 | 0.140 | 0.139 | 0.137 | 0.143 | 0.139 | 0.138 | 0.139 | 0.139 |
| Adj. $R^2$ | 0.130 | 0.131 | 0.130 | 0.127 | 0.133 | 0.129 | 0.128 | 0.130 | 0.130 |
| $\text{Coherence}_{t_0}$ (log) | −0.008 | | | −0.014** | | | 0.006 | | |
| | (0.006) | | | (0.006) | | | (0.007) | | |
| $\text{Fitness}_{t_0}$ | | −0.004*** | | | −0.005*** | | | −0.001 | |
| | | (0.002) | | | (0.002) | | | (0.002) | |
| $\text{Entropy}_{t_0}$ | | | −0.006 | | | −0.002 | | | 0.009 |
| | | | (0.006) | | | (0.006) | | | (0.006) |
| $R^2$ | 0.138 | 0.145 | 0.137 | 0.142 | 0.146 | 0.136 | 0.137 | 0.136 | 0.138 |
| Adj. $R^2$ | 0.128 | 0.136 | 0.128 | 0.133 | 0.137 | 0.126 | 0.127 | 0.126 | 0.129 |
| Observations | 657 | 657 | 657 | 657 | 657 | 657 | 657 | 657 | 657 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

# Regional productivity and skill portfolio: Long difference regression

| Dep. Variable: Δ LP (log) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ Coherence (log) | −0.009 | | | | | |
| | (0.025) | | | | | |
| Δ Fitness (log) | | −0.001 | | | | |
| | | (0.010) | | | | |
| Δ Entropy | | | 0.002 | | | |
| | | | (0.020) | | | |
| $\text{Coherence}_{t_0}$ (log) | | | | −0.000 | | |
| | | | | (0.013) | | |
| $\text{Fitness}_{t_0}$ | | | | | −0.004 | |
| | | | | | (0.008) | |
| $\text{Entropy}_{t_0}$ | | | | | | 0.002 |
| | | | | | | (0.009) |
| Observations | 166 | 166 | 166 | 166 | 166 | 166 |
| $R^2$ | 0.099 | 0.098 | 0.098 | 0.098 | 0.100 | 0.099 |
| Adj. $R^2$ | 0.059 | 0.058 | 0.058 | 0.058 | 0.060 | 0.059 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |

# Regional productivity and skill type: Panel regression with FE

| Dep. Variable: ln(LP) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| L.Digital skills share | 1.138*** | 0.131*** | 0.128*** | | | | 0.124*** | 0.101*** |
| | (0.063) | (0.023) | (0.021) | | | | (0.021) | (0.028) |
| L.Green skills share | | | | −30.326*** | −1.729** | −1.928*** | −1.765*** | −3.407** |
| | | | | (2.570) | (0.750) | (0.640) | (0.645) | (1.468) |
| Capital formation (log) | | | 0.172*** | | | 0.173*** | 0.174*** | 0.174*** |
| | | | (0.023) | | | (0.023) | (0.023) | (0.023) |
| Population (log) | | | 0.213** | | | 0.240** | 0.208** | 0.210** |
| | | | (0.099) | | | (0.099) | (0.097) | (0.097) |
| EU patents | | | 0.001 | | | 0.001 | 0.001 | 0.001 |
| | | | (0.001) | | | (0.001) | (0.001) | (0.001) |
| Skill diversity | | | 0.013* | | | 0.020*** | 0.014* | 0.013* |
| | | | (0.007) | | | (0.007) | (0.007) | (0.007) |
| Employment | | | −0.625*** | | | −0.630*** | −0.618*** | −0.621*** |
| | | | (0.072) | | | (0.073) | (0.072) | (0.072) |
| L.Digital × L.Green | | | | | | | | 8.569 |
| | | | | | | | | (6.994) |
| Observations | 3270 | 3270 | 3221 | 3270 | 3270 | 3221 | 3221 | 3221 |
| Adj. $R^2$ | 0.091 | 0.991 | 0.993 | 0.041 | 0.991 | 0.993 | 0.993 | 0.993 |
| Within $R^2$ | | 0.017 | 0.214 | | 0.005 | 0.205 | 0.220 | 0.220 |
| Region FE | NO | YES | YES | NO | YES | YES | YES | YES |
| Year FE | NO | YES | YES | NO | YES | YES | YES | YES |

Skill types scatterplots

# Regional productivity and skill type: Panel regression with FE

| Dep. Variable: LP (log) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| L.Digital skill share | 1.266*** | −0.047 | −0.000 | | | | −0.012 | −0.110 |
| | (0.175) | (0.141) | (0.138) | | | | (0.138) | (0.152) |
| L.Green skill share | | | | −12.312*** | 0.180 | −0.769 | −0.778 | −3.110** |
| | | | | (2.563) | (0.494) | (0.480) | (0.472) | (1.547) |
| Capital formation (log) | | | 0.028 | | | 0.028 | 0.028 | 0.028 |
| | | | (0.018) | | | (0.018) | (0.018) | (0.018) |
| Population (log) | | | 0.440 | | | 0.455 | 0.455 | 0.473* |
| | | | (0.276) | | | (0.278) | (0.278) | (0.280) |
| EU patents (IHS) | | | −0.002 | | | −0.001 | −0.001 | −0.002 |
| | | | (0.003) | | | (0.003) | (0.003) | (0.003) |
| Skill diversity (log) | | | −0.014 | | | −0.014 | −0.014 | −0.015 |
| | | | (0.025) | | | (0.024) | (0.025) | (0.025) |
| Employment (log) | | | −0.727*** | | | −0.731*** | −0.731*** | −0.734*** |
| | | | (0.069) | | | (0.069) | (0.069) | (0.070) |
| L.Digital × L.Green skill share | | | | | | | | 38.592 |
| | | | | | | | | (23.808) |
| Observations | 830 | 830 | 830 | 830 | 830 | 830 | 830 | 830 |
| Adj. $R^2$ | 0.058 | 0.945 | 0.956 | 0.026 | 0.945 | 0.956 | 0.956 | 0.956 |
| Within $R^2$ | | 0.000 | 0.208 | | 0.000 | 0.209 | 0.209 | 0.211 |
| Region FE | NO | YES | YES | NO | YES | YES | YES | YES |
| Year FE | NO | YES | YES | NO | YES | YES | YES | YES |

# Regional productivity and skill type: Long differences

| Dep. Variable: Δ LP (log) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ Digital skill share | 0.104* | | 0.093 | | | |
| | (0.059) | | (0.059) | | | |
| Δ Green skill share | | −3.450*** | −3.316*** | | | |
| | | (1.230) | (1.231) | | | |
| Digital skill share $t_0$ | | | | −0.008 | | −0.035 |
| | | | | (0.042) | | (0.044) |
| Green skill share $t_0$ | | | | | −2.416* | −2.725** |
| | | | | | (1.268) | (1.328) |
| Observations | 654 | 654 | 654 | 654 | 654 | 654 |
| $R^2$ | 0.141 | 0.147 | 0.151 | 0.137 | 0.142 | 0.143 |
| Adj. $R^2$ | 0.132 | 0.138 | 0.140 | 0.128 | 0.133 | 0.132 |
| Controls | YES | YES | YES | YES | YES | YES |

Green and digital decompositions

# Regional productivity and skill type: Long differences

| Dep. Variable: Δ LP (log) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ Digital skill share | −0.000 | | 0.064 | | | |
| | (0.376) | | (0.390) | | | |
| Δ Green skill share | | 1.073 | 1.148 | | | |
| | | (1.707) | (1.770) | | | |
| Digital skill share $t_0$ | | | | 0.177 | | 0.162 |
| | | | | (0.307) | | (0.313) |
| Green skill share $t_0$ | | | | | −0.671 | −0.516 |
| | | | | | (1.721) | (1.751) |
| Observations | 166 | 166 | 166 | 166 | 166 | 166 |
| $R^2$ | 0.098 | 0.101 | 0.101 | 0.100 | 0.099 | 0.101 |
| Adj. $R^2$ | 0.058 | 0.061 | 0.055 | 0.060 | 0.059 | 0.055 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |

# Conclusions

# Conclusions

- In the EU, skills coherence, fitness, and concentration are negatively associated to changes in labour productivity in the short run
  - **Mixing unrelated skills pays off**, but too **sophisticated skills do not immediately translate in productivity gains**
  - In the UK results are generally more noisy, with coherence being positively related to productivity
- More digital skills demand is associated to modest short run productivity increases
- Regions with higher demand for green skills show lower productivity growth: this effect comes particularly from greening industries rather than inherently green ones
- OJAs tends to **overrepresent service-sector** jobs and those requiring more transversal skills

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# Next steps

- Skill type: Alternate definitions (e.g. digital skills (Sostero and Tolan 2022))
- Identification strategy: shift share using the regional exposure to emerging digital technology to instrument for skill demand
- Skills demand and stock coherence

# Thank you!

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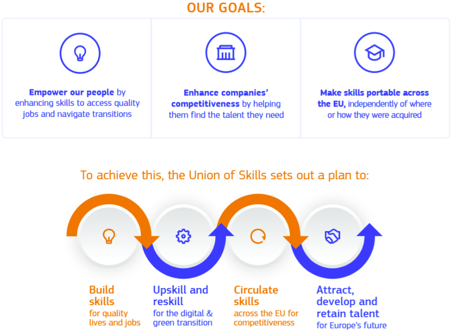
# Why skills matter for policy: the EU Union of Skills Back

- **Union of Skills**: **human capital** at the core of **competitiveness**
- Four complementary priorities:
  - **Strong skills foundations**
  - **Upskilling/reskilling** for the twin transition
  - **Circulation of skills** across the EU
  - **Attracting, developing, and retaining talent**
- Policy needs timely, granular indicators of **which skills are demanded**, **where**, and **how** skill portfolios relate to productivity




Sources: European Commission (2025), Union of Skills (Communication + Press release). commission.europa.eu/topics/competitiveness/union-skills

# Skill spaces Back

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- Alabdulkareem et al. 2018 divides between socio-cognitive and sensory-physical skills
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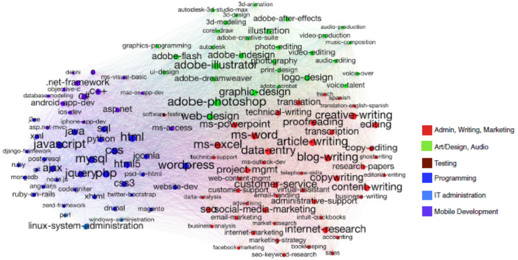

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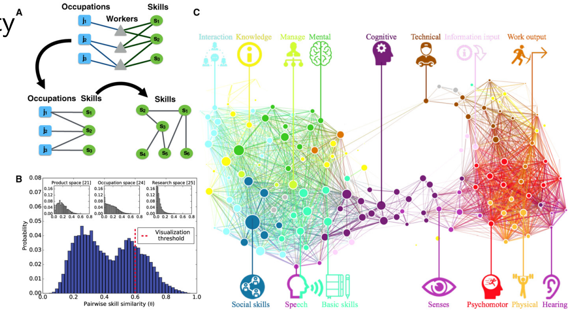

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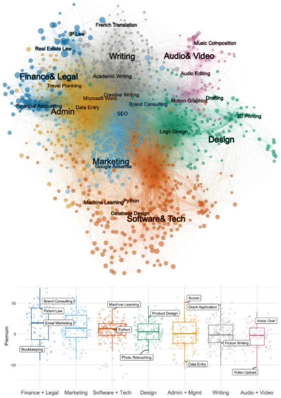

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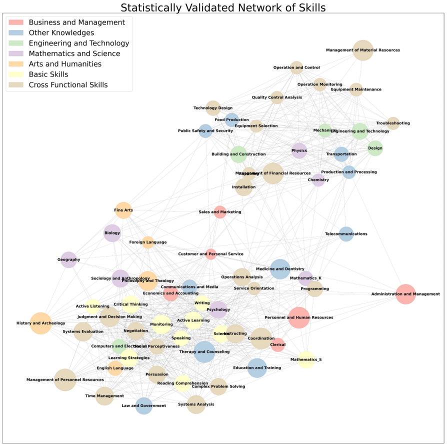

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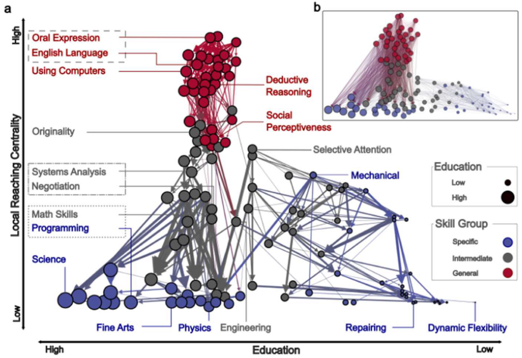


# ESCO skill pillar

Back

**Search skills**

Search ...

Find

Show filters

- T - transversal skills and competences +
- S - skills +
- K - knowledge +
- L - language skills and knowledge +

**13939**

Skills

The skills pillar provides a comprehensive list of knowledge, skills and competences relevant to the European labour market. In ESCO v1.2.0, the skills pillar is structured in a hierarchy which contains the following four sub-classifications:

- **Knowledge**
- **Language skills and knowledge**
- **Skills**
- **Transversal skills**

# Green and digital skills: examples

Back

| Green skills (ESCO Green label) | Digital skills (ESCO Digital / DigComp label) |
|---|---|
| Conduct energy audits | Implement ICT risk management |
| Improve energy efficiency | Identify ICT security risks |
| Develop recycling programmes | Handle cybersecurity incidents |
| Train staff on recycling programmes | Perform ICT security testing |
| Develop waste management processes | Develop information security strategy |
| Develop hazardous waste management strategies | Implement cloud security and compliance |
| Develop non-hazardous waste management strategies | Manage standards for data exchange |
| Implement sustainable tourism practices | Apply data protection principles |
| Assess environmental impact | Develop and maintain databases |
| Apply circular economy principles | Develop software applications |

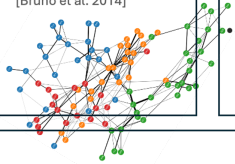
# Methods for skill demand characteristics by S, K, T and overall

Back

**Skill portfolio**

**1) Network**

1. **Occupation-skill** [Zaccaria et al. 2014]
2. **Validate network** by BiWCM for Inferred Comparative Advantage (**ICA**) [Bruno et al. 2014]



**2) Network indices**

- **Coherence:** The relatedness of skills within regions [Aufiero et al. 2014]
- **Fitness:** The sophistication of skill portfolios [Hidalgo & Hausmann, 2007; Tacchella et al. 2012]
- **Entropy:** The dispersion of skill distribution in regions [Frenken et al., 2007]

**Skill types**

**From ESCO (v1.2.0) list:**

- Green skills
- Digital skills

**Regressions**

Separately for portfolio & types:

**1) FE panel regression**

$$LP_{rt} = \alpha + \beta \mathbf{SP_{rt}} + \gamma \mathbf{ST_{rt}} + \theta \mathbf{X_{rt}} + \sigma_r + \tau_t + \epsilon_{rt}$$

**2) Long-difference regression**

[Acemoglu & Restrepo, 2019]

$$\Delta LP_{r,T-t} = \alpha + \beta \Delta \mathbf{SP_{r,T-t}} + \gamma \Delta \mathbf{ST_{r,T-t}} + \theta \mathbf{X_{r,2014}} + \epsilon_r$$

*LP*: labour productivity, *SP*: portfolio characteristics, *ST*: skill types, *X*: controls (time-varying or baseline), $\sigma_r$: region FE, $\tau_t$: year FE

# Classifying Lightcast skills using ESCO

Back

Combine exact matching and similarity between word embeddings of OJA and ESCO description

**(i) String comparison**

1,747 Lightcast skills on ESCO Preferred Labels (v1.2.0):

→ 1,279 matched; *468 remain*

**(ii) Vector comparison**

Unmatched skills on Preferred Labels by:

- Cosine similarity of OpenAI embeddings
- Similarity > 0.70 accepted, similarity 0.66-0.70 manually reviewed for acceptance

→ 212 matched; *256 remain*

**(iii) Manual review**

Manually review top-3 similar Preferred Labels by:

- Skill-occupation network
- Own knowledge
- Defined ChatGPT-4o prompt

Match if at least two reviewers confirm a Preferred Label.

→ 187 matched; *69 remain*

Manually distinguish:

- Ambiguous skills (dropped): 12
- Non-software skills (labelled manually): 12
- Software skills → *45 remain*

**(iv) Unmatched software: Vector & manual**

1. Vector comparison (see (ii))

50-word ChatGPT-4o descriptions of software skills on ESCO Preferred Labels descriptions:

→ 0 matched; *45 remain*

2. Manual review (see (iii))

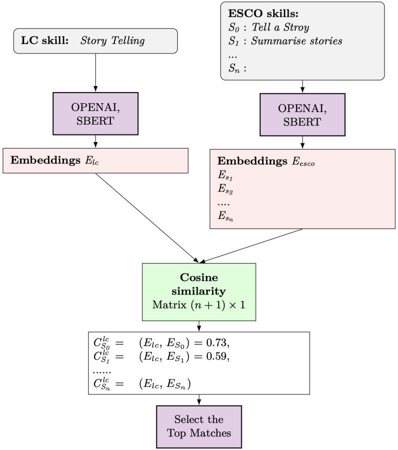
→ 38 matched; *7 remain*

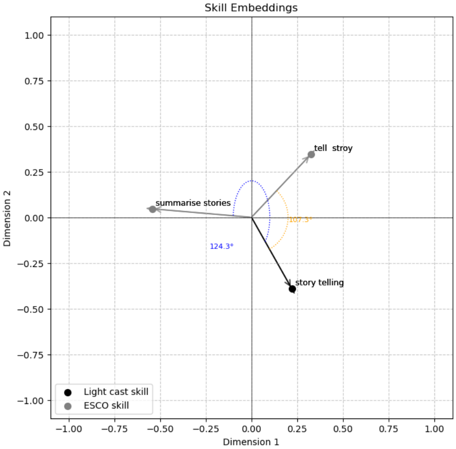
3. Manual labels for remaining

→ 5 matched, 2 dropped since ambiguous

# Similarity using word embeddings

Back



# Regional skills specialisation

Back

We aim to identify the skills that regions demand significantly more than other regions.

Two specialisation measures:

- Revealed Comparative Advantage (RCA) (Balassa 1965)
- **Inferred** Comparative Advantage (ICA), based on Bipartite Weighted Configuration Model (BiWCM) (Bruno et al. 2023)

Generalisation of specialisation measures:

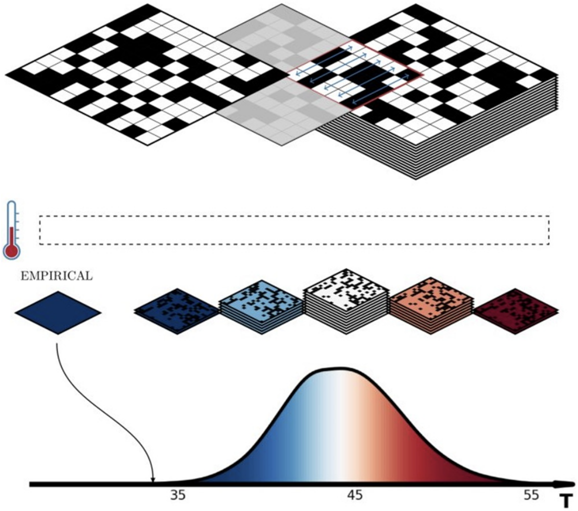
$$CA_{r,s} = \frac{X_{r,s}}{\mathbb{E}[X_{r,s}]} \tag{1}$$

# Regional skills specialisation

Back

- The expected value in RCA is based on the assumption that each country's export distribution is independent of the global distribution, essentially using a naïve baseline that preserves row and column sums
- ICA uses a statistical model that accounts for the correlation between countries' total export capacities and the global trade volumes of products. It assigns statistical significance to observed trade relationships, providing a more nuanced understanding of specialisation

# BiWCM Back



# BiWCM: toy example Back

$V_{ab}$

| | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|
| $a_1$ | 10 | 5 | 7 | 2000 |
| $a_2$ | 30 | 1 | 2 | 1 |
| $a_3$ | 20 | 3 | 0 | 55 |

$$RCA_{a_1 b_2} = \frac{5/2022}{6/2056} = 0.85$$

$ICA_{ab}$

| | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|
| $a_1$ | 0.33 | **1.55** | **2.17** | **1.01** |
| $a_2$ | **2.71** | 0.37 | 0.73 | 0.57 |
| $a_2$ | **1.04** | 0.99 | 0.00 | **1.04** |

$RCA_{ab}$

| | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|
| $a_1$ | 0.18 | 0.59 | 0.82 | **1.03** |
| $a_2$ | **31.4** | **6.97** | **13.9** | 0.03 |
| $a_3$ | **9.12** | **9.12** | 0.00 | 0.73 |

$M_{ab}$

| | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|
| $a_1$ | 0 | 1 | 1 | 1 |
| $a_2$ | 1 | 0 | 0 | 0 |
| $a_3$ | 1 | 0 | 0 | 1 |

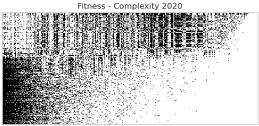
$M_{ab}$

| | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|
| $a_1$ | 0 | 0 | 0 | 1 |
| $a_2$ | 1 | 1 | 1 | 0 |
| $a_3$ | 1 | 1 | 0 | 0 |

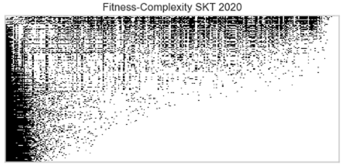
# Regional specialisation Back

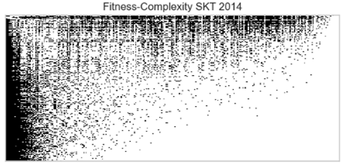
Identify the skills that regions demand significantly more than other regions: Balassa Index (Balassa 1965), Bipartite Wheighted Configuration Model (BiWCM) (Bruno et al. 2023)

**Balassa Index**


**BiWCM**

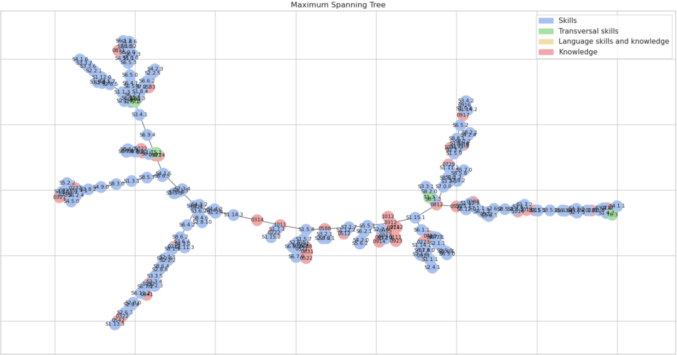


# Skills network Back

We are interested in measuring the closeness of skills, based on their co-occurrence in a region

Skills that co-occur across different regions are likely to be demanded together, and therefore show some degree of proximity (Zaccaria et al. 2014)



# Skills network

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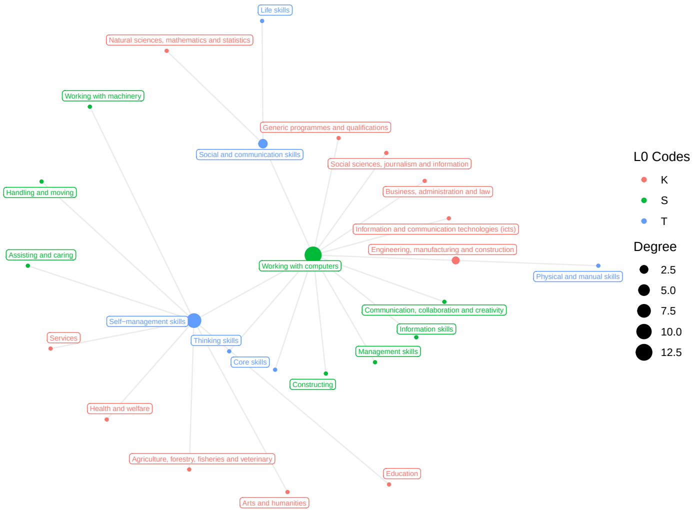

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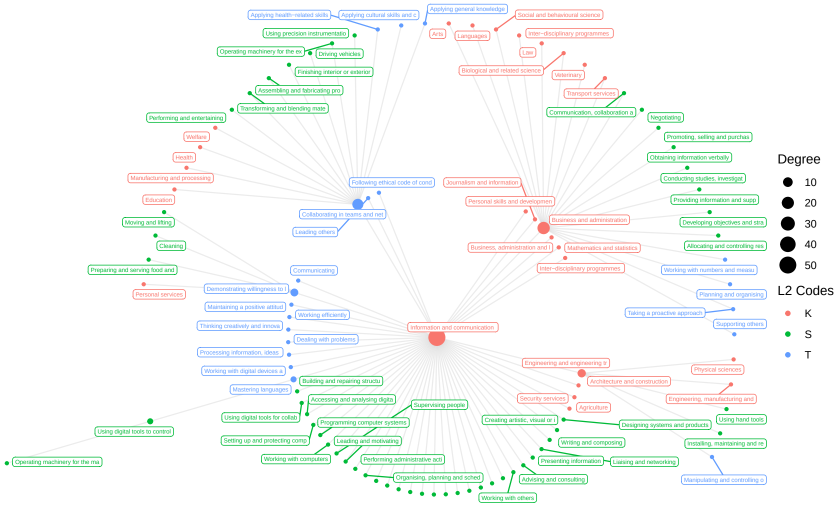

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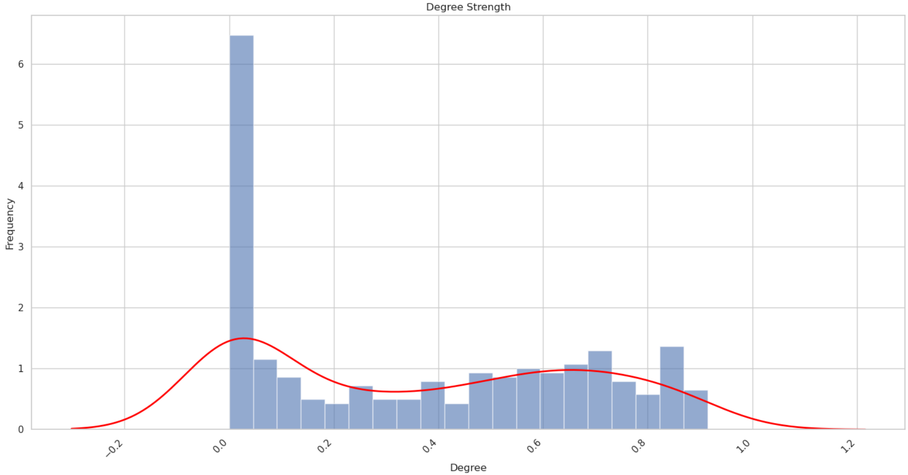
Back



# Top 10 Skill Pairs by Edge Weight Back

| Skill 1 | Skill 2 | Weight |
|---|---|---|
| measuring physical properties | using precision measuring equipment | 0.171429 |
| managing transport and logistics activities | driving heavy vehicles | 0.145342 |
| child care and youth services | caring for children | 0.125280 |
| hotel, restaurants and catering | travel, tourism and leisure | 0.123075 |
| repairing and installing mechanical equipment | maintaining mechanical machinery | 0.113988 |
| presenting information in legal proceedings | executing financial transactions | 0.107565 |
| monitoring, inspecting and testing | monitoring safety or security | 0.105321 |
| monitoring financial and economic resources and budgets | operating food processing machinery | 0.100467 |
| determining values of goods or services | operating food processing machinery | 0.094709 |
| teaching and training | coaching and mentoring | 0.089527 |

# Bottom 10 Skill Pairs by Edge Weight Back

| Skill 1 | Skill 2 | Weight |
|---|---|---|
| providing information to the public and clients | shaping materials to create products | 0.000972 |
| providing information to the public and clients | managing and administering human resources | 0.001074 |
| occupational health and safety | creating artistic, visual or instructive materials | 0.001082 |
| creating artistic, visual or instructive materials | shaping materials to create products | 0.001082 |
| language acquisition | business, administration and law nec | 0.001087 |
| business, administration and law nec | information and communication technologies nec | 0.001087 |
| business, administration and law nec | presenting research or technical information | 0.001087 |
| business, administration and law nec | performing calculations | 0.001087 |
| business, administration and law nec | verifying identities and documentation | 0.001087 |
| performing calculations | developing educational programmes | 0.001115 |

# Coherence

Back

**Coherence** (Aufiero et al., 2024) measures how related skills demanded by a region are, based on how likely are all skill pairs to occur **in the same occupation**.

Originates from the $M_{rs}$ matrix (region-skill specialisation matrix):

$$\text{Coherence}_r = \frac{\sum_{s,s'} M_{rs} M_{rs'} B_{ss'}}{\sum_{s,s'} M_{rs} M_{rs'}}$$

Where $B_{ss'} = M_{os} M'_{os}$, i.e. the bipartite projection of an occupation-skill matrix, measuring the probability for two skills to occur more than randomly **in the same occupation** (ISCO 4 digit)

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# Fitness Back

The Fitness and Complexity algorithm (Tacchella et al., 2012) measures the sophistication of regions based on the number and uniqueness of the skills they demand:

$$\widetilde{F}_r^{(n)} = \sum_s M_{r,s}\, Q_s^{(n-1)} \tag{2}$$

$$\widetilde{Q}_s^{(n)} = \frac{1}{\sum_r M_{r,s} \frac{1}{F_r^{(n-1)}}} \tag{3}$$

- Regions are 'fitter' (F) if they demand many skills, and if these skills are hard to find in the demand of other regions
- Skills are more complex (Q) if they are non-ubiquitous, and if the regions that demand them are also very diversified

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- Skills are more complex (Q) if they are non-ubiquitous, and if the regions that demand them are also very diversified

# Entropy

Back

We assess the degree of concentration (or, conversely, concentration) of regional skill demand using an entropy-based index Frenken et al. (2007).

Formally, the entropy of region $r$ is defined as:

$$\text{Entropy}_r = \sum_s p_{rs} \ln\left(\frac{p_{rs}}{\bar{p}}\right) \tag{4}$$

where $p_{rs}$ denotes the share of demand for skill $s$ within the total skill demand of region $r$, and $\bar{p}$ is the average share of all skills.

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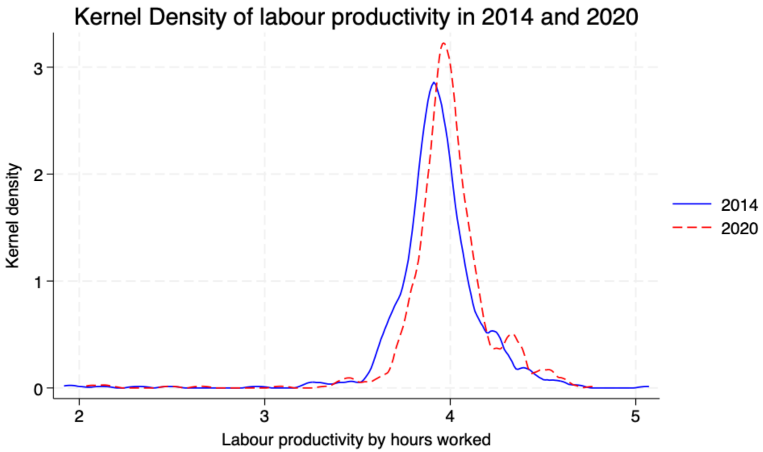
# Labour Productivity Back

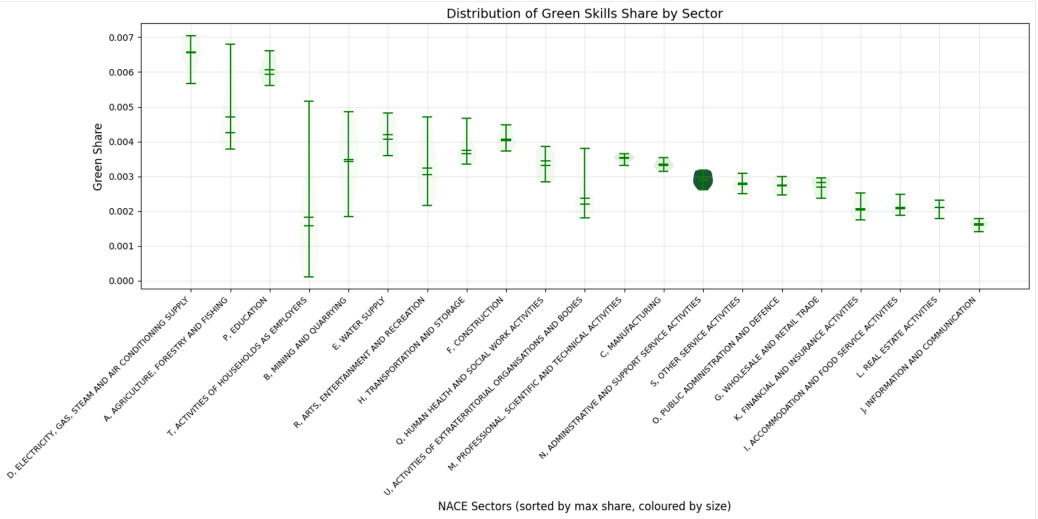


# FE regression with first lag of labour productivity

| VARIABLES | (1) |
|---|---|
| L.LP | 0.647*** |
| | (0.0155) |
| Constant | 1.383*** |
| | (0.0602) |
| Observations | 3,870 |
| Number of region id | 645 |
| Within R-squared | 0.352 |
| Adj R-squared | 0.222 |
| N | 3,870 |

# Green decomposition

Back



# Green decomposition

Back

$$S_t - S_T = \underbrace{\sum_{j=1}^{J} \left( \frac{w_{jt} + w_{jT}}{2} \right) (s_{jt} - s_{jT})}_{\text{Within}} + \underbrace{\sum_{j=1}^{J} \left( \frac{s_{jt} + s_{jT}}{2} \right) (w_{jt} - w_{jT})}_{\text{Between}}$$

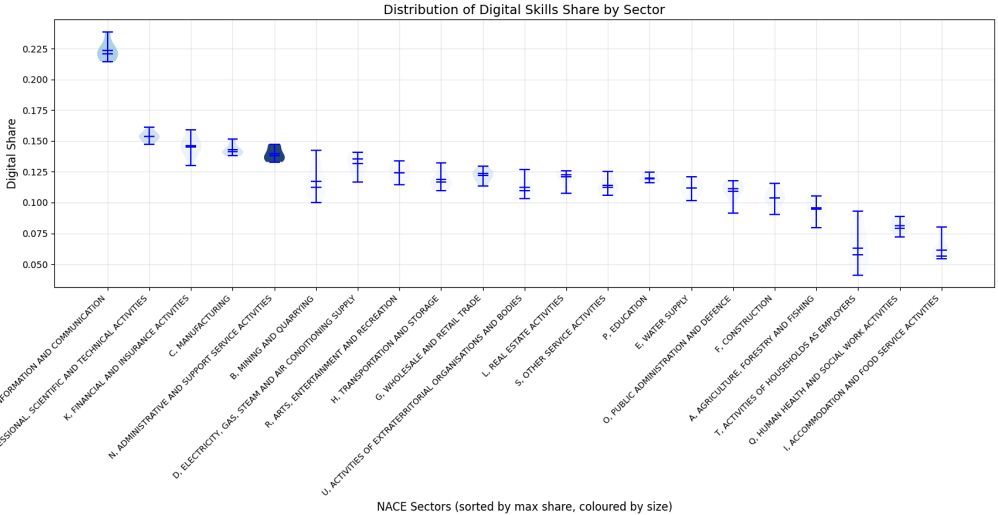
Table: Shift–Share Decomposition of change Green Skill Demand 2014-2019 (NACE 1-digit)

| Component | Contribution |
|---|---|
| Total change | 0.0008 |
| Within-industry | 0.0009 |
| Between-industry | -0.0001 |

Notes: Percentages indicate each component's contribution relative to the total change. Values exceeding 100% arise when within- and between-industry components reinforce each other or offset small total changes.

# Digital decomposition

Back



# Digital decomposition

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Table: Shift–Share Decomposition of change in Digital Skill Demand 2014-2019 (NACE 1-digit)

| Component | Contribution |
|---|---|
| Total change | 0.0119 |
| Within-industry | 0.0115 |
| Between-industry | -0.0011 |

Notes: Percentages indicate each component's contribution relative to the total change. Values exceeding 100% arise when within- and between-industry components reinforce each other or offset small total changes.

# Skills stock

- So far we have focused on the characteristics of **demanded skills portfolio**
- However, it remains to be seen how the demand is coherent with the **stock of pre-existing skills** in regions
- **Pilot**: assess the coherence between demand and stock of skills using Swedish data
- Stock of skills inferred using occupational structures of regions, and mapping of the occupations to skills
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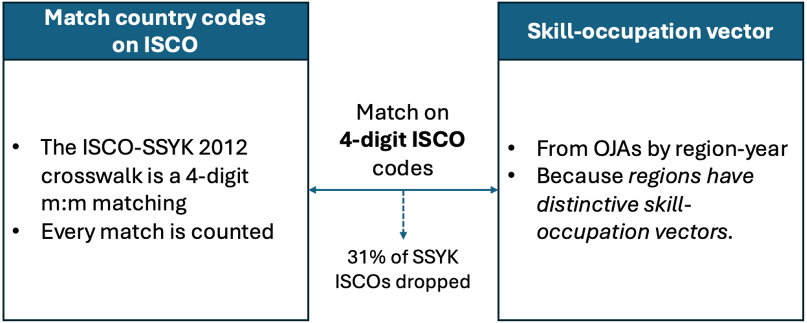
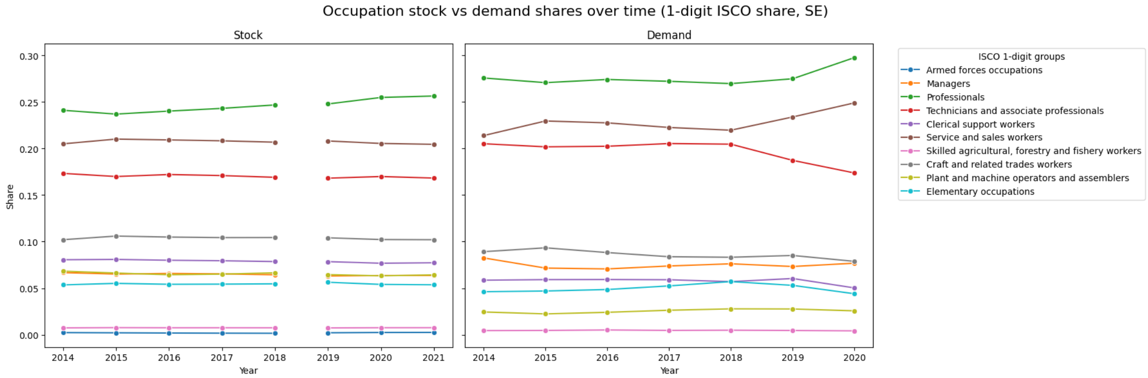
# Creating the skill stock vector



# Skill stock vs demand: ISCO 1-digit shares (Sweden)

Professionals, Service and Sales workers, and Managers are overrepresented in OJAs:




Because the method for calculating Swedish skill stock data changed in 2018, the sample is split into 2014-2018 and 2019-2021.

# Skill stock vs demand: Skills, Knowledge Transversal skills (Sweden)

Occupations requiring transversal skills are overrepresented in OJAs: