Emerging Practices and Methods for Skills Intelligence Inside and Outside the Academy

WARWICK
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SKILLS - PREDICTING, UNDERSTANDING, AND LOCATING SHORTAGES IN EUROPE

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What do we want to know?

- Prediction of skills required in the future…
- … and which skills will become obsolescent
- Identification (and anticipation) of skill mismatches
- Skills to be included in curricula
- Skills for growth
- Skills to support the twin green and digital transitions
- How skills and automation might redress population stagnation and decline (fewer people, more machines, different skills?)
- Skills as a panacea

Assumptions

- Assumptions that sometimes underlie approaches to skills analysis
  - Change is rapid (the evidence is a little uncertain here)
  - Skills shortages are a drag on growth (it tends to be surpluses rather than shortages that is the problem in search of a solution)
  - Skills stimulate growth (yes, but much else needs to be in place as well. After all skill is a derived demand)
  - Skills generates a financial return (but estimates are for average rather than marginal returns)
  - The returns one person obtains from a particular skill will be obtained by another person should they acquire those skills (a heroic assumption)

We need to know something about skills, but what is a skill?

- In his seminal review What is Skill? Paul Attewell observes that ‘like so many common sense concepts, skill proves on reflection to be a complex and ambiguous idea.’
- Often defined with reference to competence which in turn is seen to consist of:
  - **skill** - being able to practically do something such as open-heart surgery or cutting someone’s hair
  - **knowledge** - the theoretical understanding that supports practical application
  - **ability** - the capacity to undertake tasks well (however that might be defined)
- It is something that it is acquired through learning or training
- Or may be, skills simply reflects relative wage levels. A high skilled job is a relatively high paid one
- The policy discourse increasingly defines skill with reference to something which has economic value (the demand led approach)

How will the data be used?

- Planning – how many people study *x*, in location *y*
- Providing the market with labour skills intelligence (part of the demand led approach of flooding the market with information)
    - Inform employers about skill needs
    - Provision of career guidance
    - Information for course design
- Migration Policy
- Redress skill mismatches
- Just part of the statistical stock of information
- To inform / support industrial strategies

What kind of skill data are collected

- Stocks and flows

Measure	Type
Occupation	Statistical measures
Qualification	
Duration of education	
Self-assessment	Subjective measures
Skill tests	Objective measures
Job requirements	Objective / subjective?

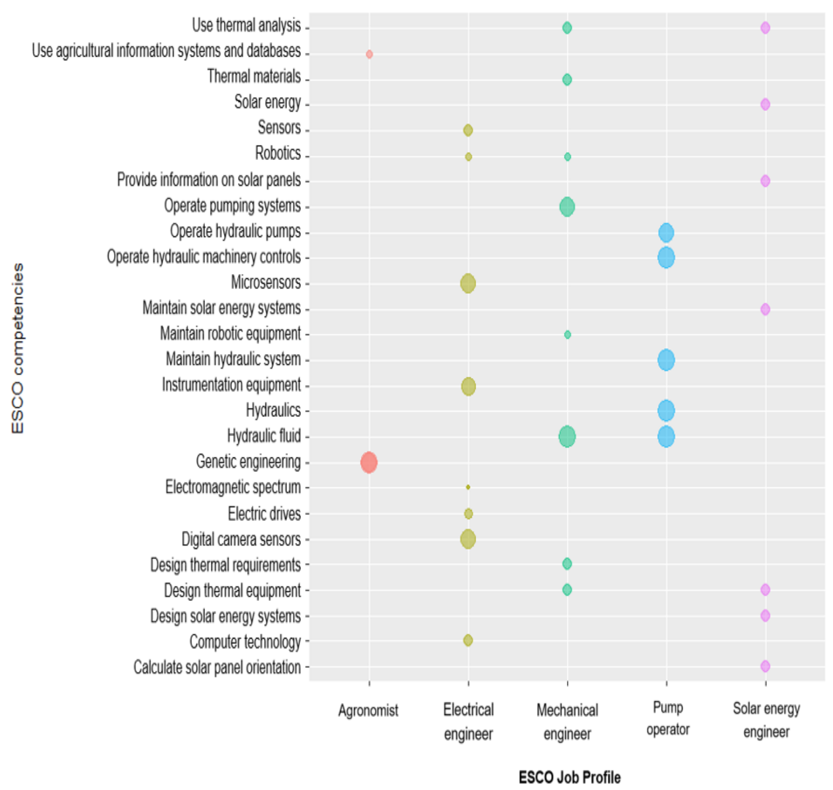
Data collections

- Linked administrative databases (pupil data, tax data, etc…)
- Surveys
  - Employers
  - Workers
  - Students
  - Tracker surveys (sample attrition is usually severe)
- Skill tests
- Case studies
- Natural language processing

The Unique Contribution of Natural Language Processing

- Provides unique data on specific skill needs
- Various sources of textual data collected and classified including demand side data (OJAs, patent data) and supply-side (CVs, curricula)…
- … allowing demand and supply sides to be compared
- Allows data to be analysed where data are otherwise scarce
- Provides data on skills rather than occupations or qualifications
- Some concerns about the veracity of the data provided (e.g. OJAs represent a wish list rather than actual skill needs)
- Still in its infancy, but undoubtedly the future

Skill Needs in the Agri-food Sector – Morocco (ETF, 2024)



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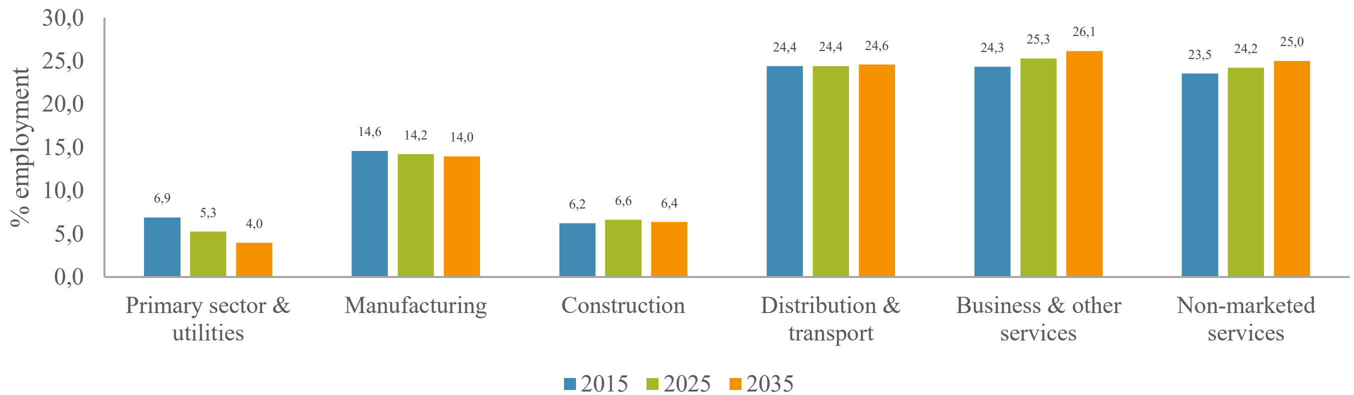
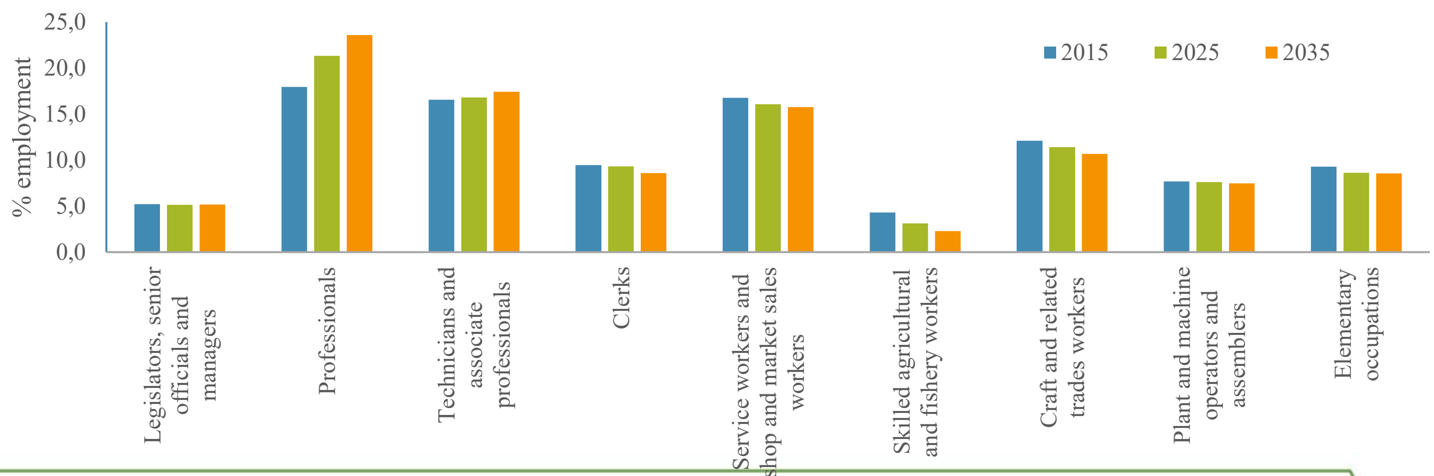
What do we know so far?

- Forecasts of future demand
- The scale of mismatches
- Skills and technological change
- Polarisation, digital skills divide, and social exclusion
- Green skills
- Returns to different types of skills / training / education
- Rates of return

The future looks a lot like the past





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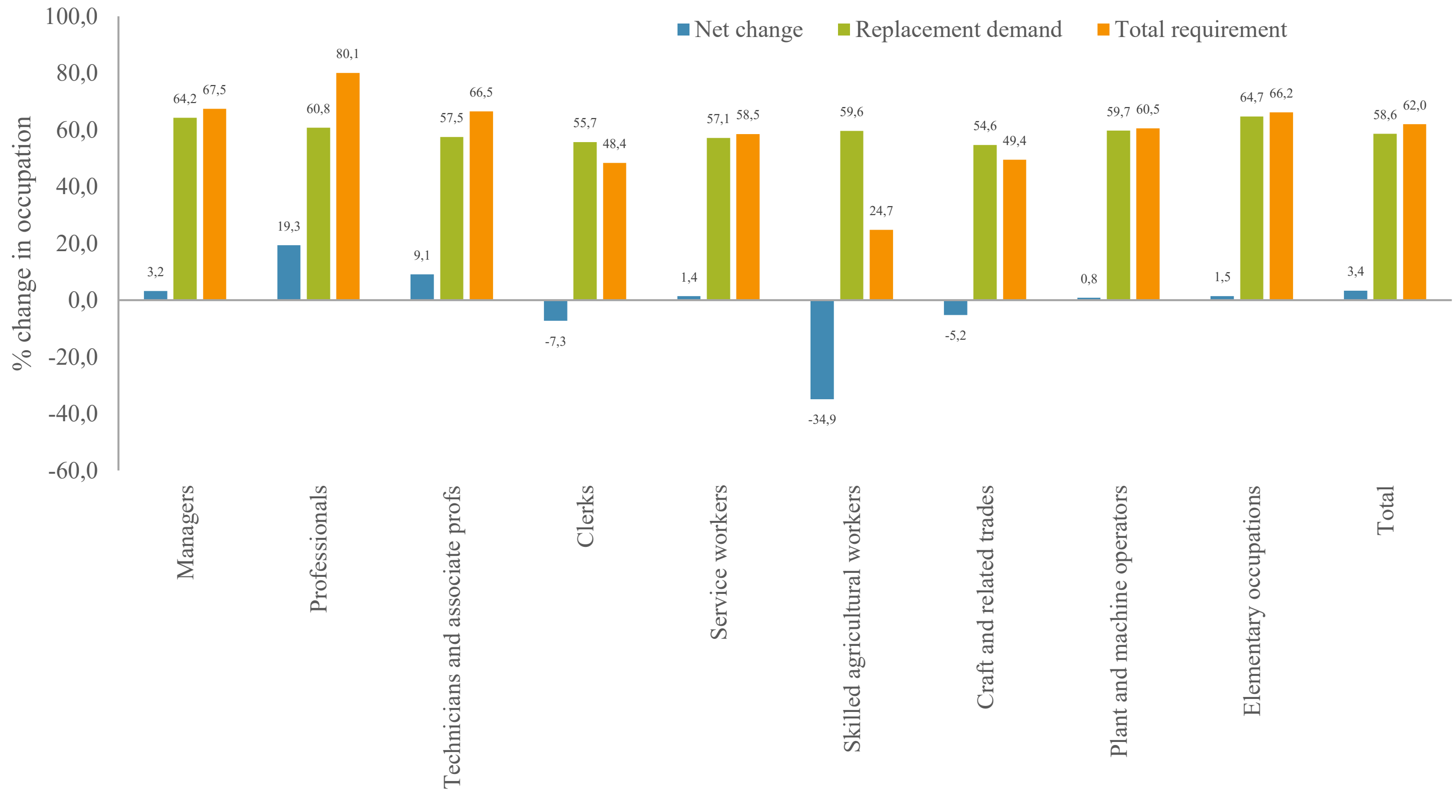
… especially when replacement demands accounted for



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Reflecting on forecast data

- Provides an indication of direction of change and scale of change
- Provides some opportunity for scenario development (but these tend to show relatively small-scale changes on occupational skill demand)
- Provides a basis for thinking about where further information might be needed about skill change
- The rush to granularity…
- … detailed information on jobs (because this focuses on the specific tasks and skills an individual will need to acquire)…
- … but can lead to being ‘not able to see the wood for the trees’

More in-depth focus on jobs

In-demand jobs (i.e. focusing on those jobs which are growing rapidly) Surprises?

Senior care workers	1.49
Rail construction and maintenance operatives	1.21
Care workers and home carers	1.19
Veterinarians	1.15
Rail transport operatives	1.13
Waste disposal and environmental services managers	1.02
Financial and accounting technicians	1.01
Directors in logistics, warehousing and transport	0.95
Farm workers	0.94
Houseparents and residential wardens	0.87
Electrical engineers	0.84
Debt, rent and other cash collectors	0.83
Office supervisors	0.81
Butchers	0.75
IT user support technicians	0.74
Other researchers, unspecified discipline	0.69
Train and tram drivers	0.68
Sales accounts and business development managers	0.65
Electrical service and maintenance mechanics and repairers	0.6
Archivists, conservators and curators	0.6
Crane drivers	0.6
Insurance underwriters	0.59
Groundworkers	0.59
Optometrists	0.59
Senior officers in fire, ambulance, prison and related services	0.58
Vehicle valeters and cleaners	0.56
Clinical psychologists	0.55
Exam invigilators	0.54

Calculation

Department for Education

- Composite indicator based on:
- **Visa application density**. The number of visa applications as a proportion of employment.
- **Skills shortage vacancy density.** The number of vacancies employers have indicated are due to a skills shortage as a proportion of all vacancies.
- **Online job advert density.** The number of online job adverts for an occupation as a proportion of employment.
- **Annual change in hourly wage.** The year-on-year change in average hourly wage in an occupation.
- **Wage premium.** The average wage of an occupation compared to other occupations at the same when controlling for factors such as age and sex.
- **Annual change in hours worked.** The year-on-year change in average weekly hours worked in an occupation. Annual change in contract or temporary workers
- The year-on-year **change in the number of contract or temporary workers** as a proportion of employment across those years.

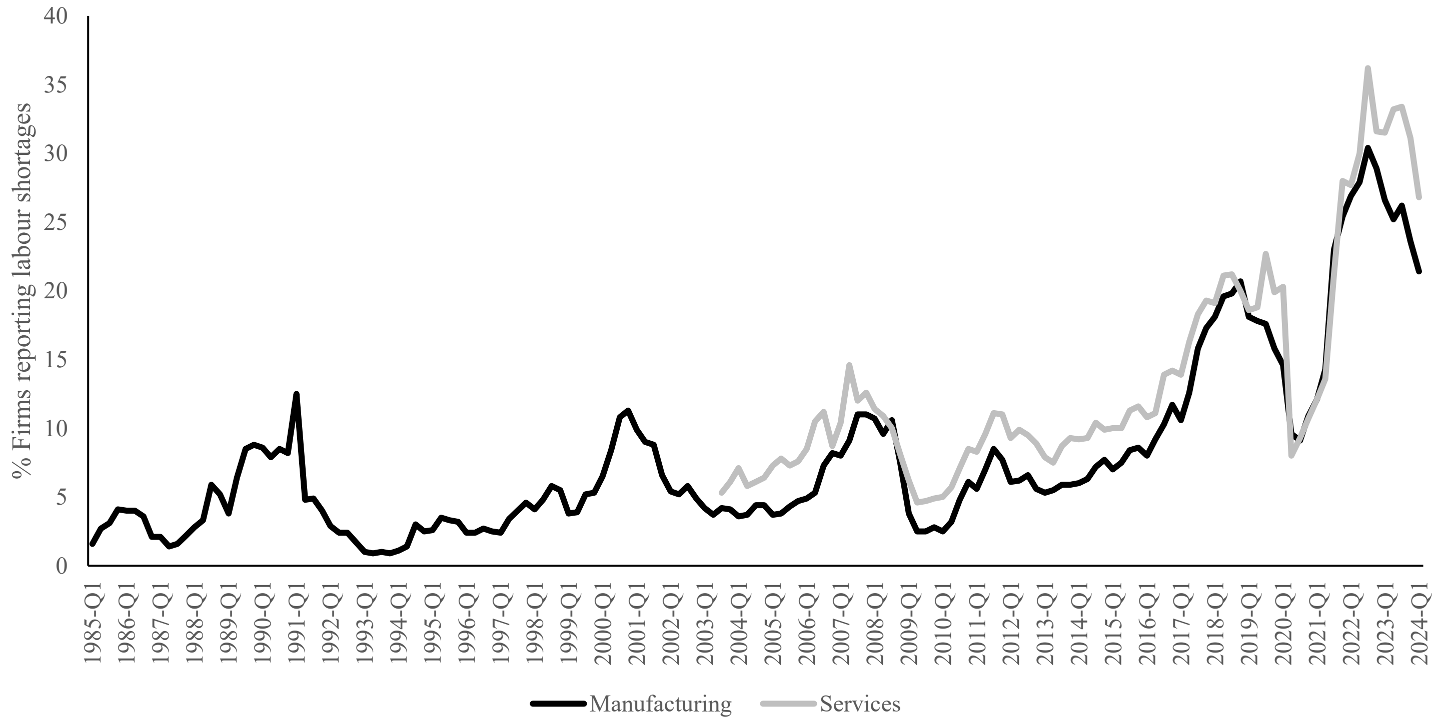
Source: Department for Education (2024) *Occupations in demand in 2024: Technical report*. London DfE

More focus on identifying job content / requirements in real-time: Example from Poland's AI sector

Data engineering	Natural language processing	Computer vision	Machine learning
• Ability to work in a Kubernetes environment • Knowledge in creating data flows using Airflow, Spark • Knowledge of Big Data tools, e.g.: Cloudera, Hortonworks Data Platform, BigQuery, Snowflake • Programming skills in Python or Scala • Knowledge of the SQL query language • Ability to design and develop data processing processes • Knowledge of databases: relational (PostgreSQL) and NoSQL (MongoDB) • English language literacy • Knowledge of ETL/ELT and data migration • Ability to work with Microsoft Azure	• Ability to collect data from the Internet and search for information • Knowledge of machine learning algorithms • Knowledge of NLP tools and algorithms • English language literacy • Knowledge of the Linux operating system • Knowledge of tools: Numpy, Scikit-learn, Tensorflow, PyTorch, Keras, Pandas, Caffe • Knowledge of Git and GitHub • Knowledge of Docker or similar tools • Python programming skills • Knowledge in data engineering and/or data science	• Python programming skills • Ability to create algorithms and work with OpenCV • English language literacy • Knowledge of the areas: computer vision, machine learning & image processing • Knowledge of Docker or similar tools • Embedded computer vision • Ability to design and implement CV models and algorithms • Knowledge of cloud solutions for machine learning • Analytical thinking • Knowledge of machine learning and deep learning algorithms	• Ability to process data for data science projects • Ability to create and optimize statistical models and AI/ML algorithms • Knowledge of machine learning algorithms • Knowledge of Git and GitHub • Knowledge of Docker or similar tools • Knowledge of statistics • Knowledge of Power BI software • Knowledge of Azure Machine Learning • Programming skills in Python, R, SQL • Ability to process different types of data

Source: Pater, R. Cherniaiev, H. and Arendt, L. (2024) 'Demand for Skills in AI-related Occupations: Polish and European perspectives' in Baltina, L. and Hogarth. T. (eds.) *Rethinking Europe's Skill Needs: Reflections following the European Year of Skills*. Rome: FGB Quaderni

Skill shortages or labour shortages I?



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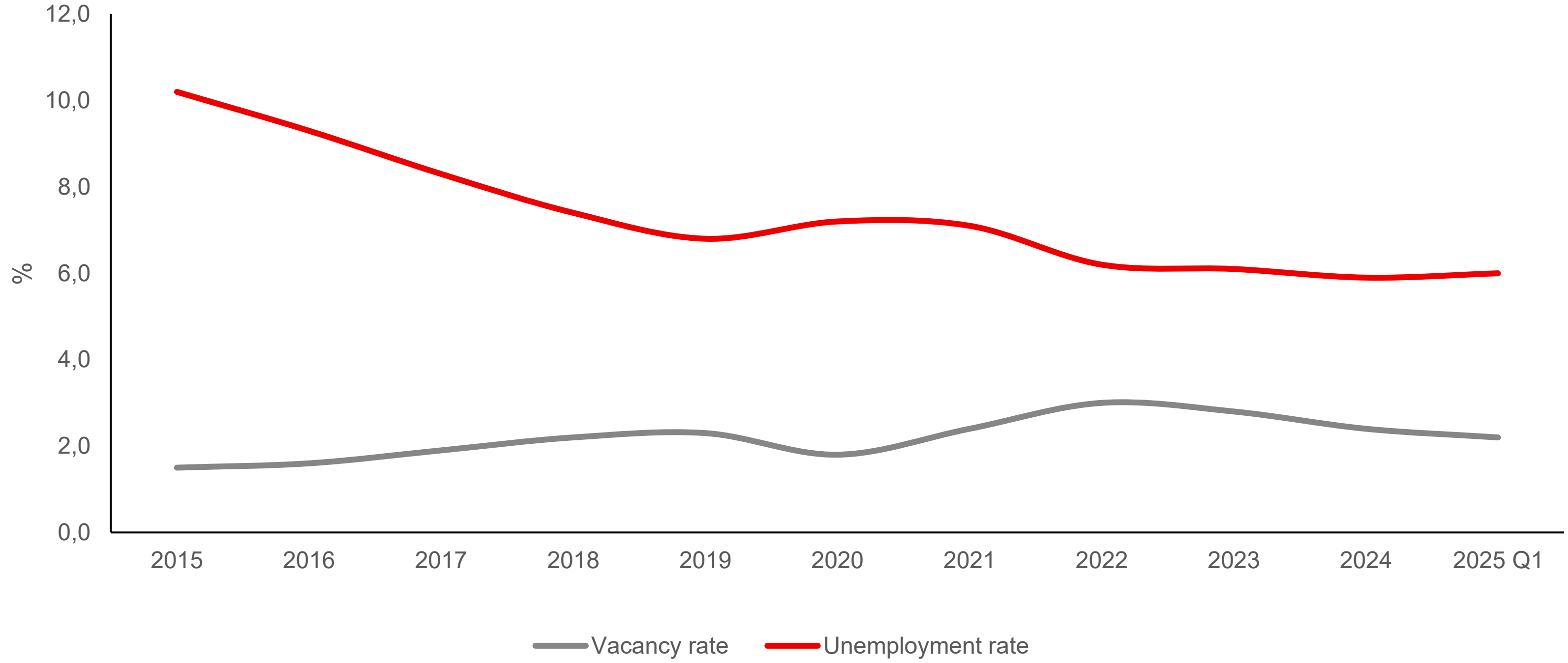
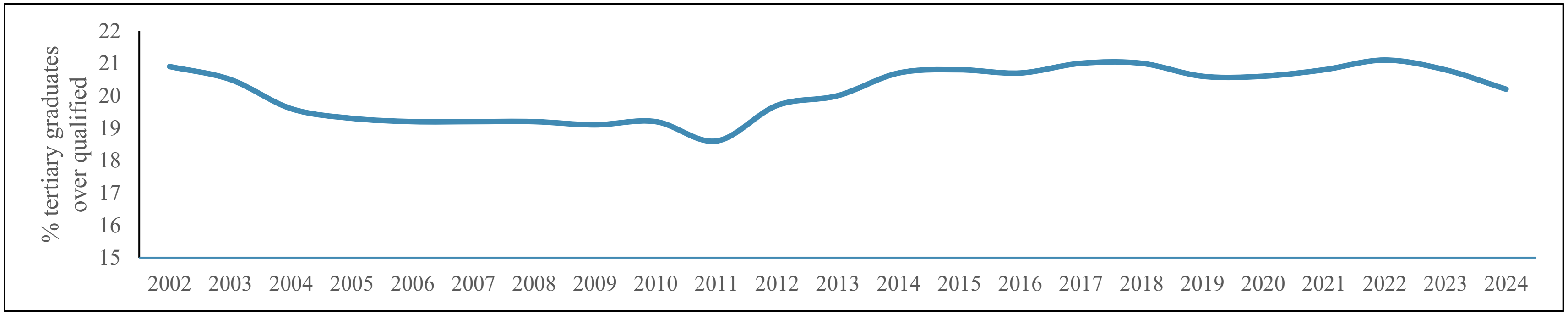
Skill shortages or labour shortages II?



Source: Eurostat job vacancy rate - annual data [jvs_a_rate] and Eurostat unemployment rate - annual data [une_rt_a]

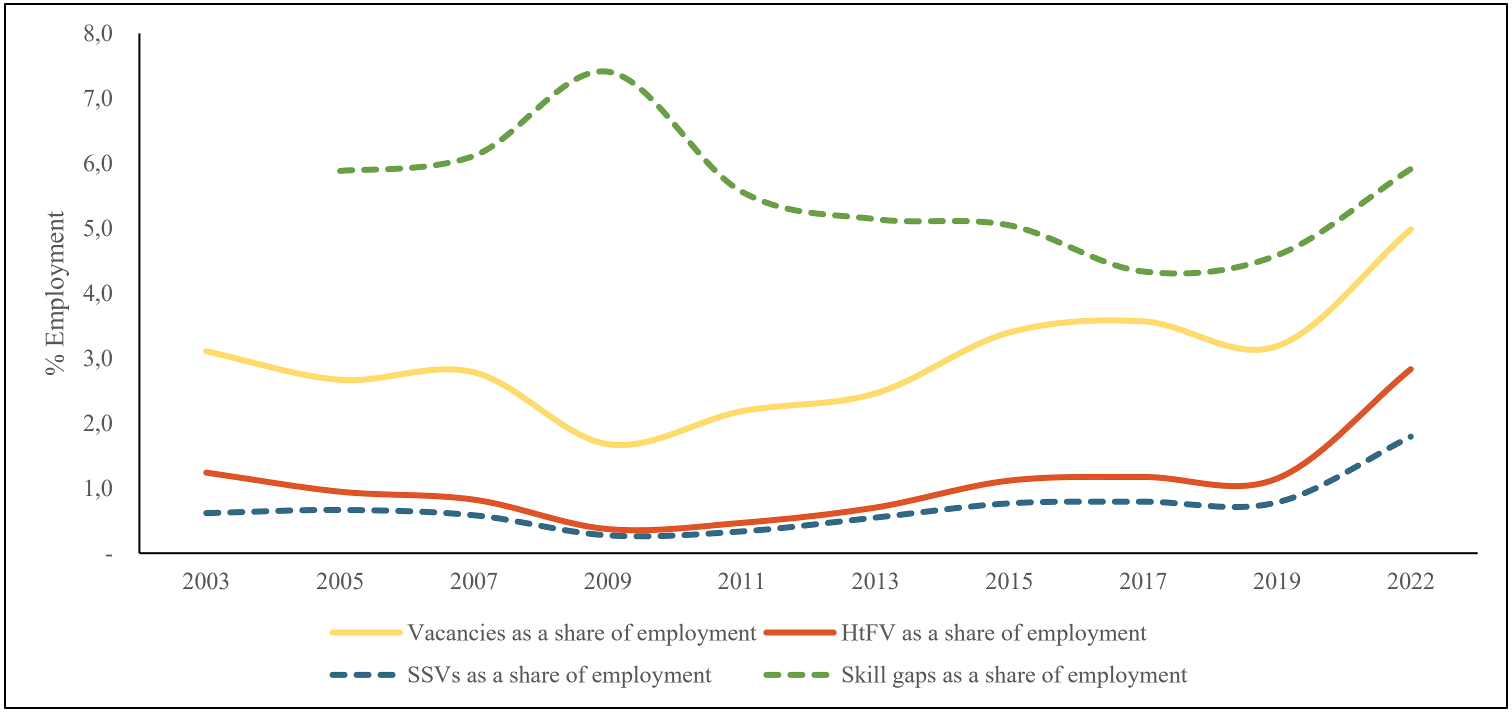
Can skill needs to be met?



Evidence from the European Skills and Jobs Survey

- The education level of four in 10 workers is not matched to that required by their job: 28% is over-qualified and 12% is under-qualified.
- Non-users of digital devices and workers less exposed to learning new digital technologies are more likely to be over-qualified.
- Over-qualified perceive less scope for further developing their skills to improve job performance compared to matched and under-qualified adult workers
- Skilled workers more likely to report an unmet need for training. Those in less skilled jobs are less likely to report unmet training needs
- Econometric evidence suggests that those who are less skilled without access to training are more likely to face some of their tasks being lost (and not replaced with new tasks) – rather than skills polarisation

Evidence for England: Employer Perspectives (Employers Skills Survey)



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Further evidence on skill mismatches

Econometric evidence from SkillsPulse study based on analysis of the European Skills and Jobs Survey (McGuinness and Staffa, 2024; McGuinness et al., 2024).

- Develops a measure of job complexity (based on intensity of skill use and level at which skills required)
- Skills gaps associated with job complexity and recognition by workers that they need to improve their skills
- No evidence that skill gaps associated with negative productivity impacts (proxied by wages) – more complex jobs generate a wage premium (other things being equal)
- Suggests that skills gaps may be non-essential with respect to doing one's job
- Suggests that market responds to labour demand?

Sources:

McGuinness, S., and Staffa, E. (2024) *D2.2 Empirical Investigation of Skills Gaps in Europe*. SkillsPulse Report

McGuinness, S., Staffa, E., and Redmond, P. (2024) 'Is there is a skills problem in Europe' in Baltina, L. and Hogarth. T. (eds.) *Rethinking Europe's Skill Needs: Reflections following the European Year of Skills*. Rome: FGB Quaderni

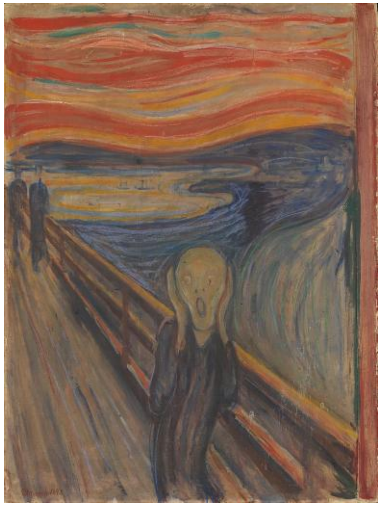
Skills and Technological Change

Lots of apocalyptic commentary on the impact of automation and AI on jobs

Analytically the interest is in:

i. automation – where machines take over some or all of the tasks undertaken in a job;
ii. augmentation – where the same machines complement the tasks undertaken by workers such that their productivity increases; and
iii. task reinstatement – where new tasks or new jobs emerge as a consequence of new technologies being introduced

- Data and analysis tends to focus on (i) and (ii) rather than (iii). In other words, we are not that sure about what the new jobs look like!



The Green Transition

- It is difficult to pinpoint the skill impact of the green transition
- The emergence of new types of skill requirements is far from evident
- The evidence points to it having a relatively modest impact on occupational change – more about adapting existing jobs at the margin

Recap

- Concepts remain fuzzy (especially definition of skill) but consensus that skill intensity of employment is increasing
- Diagnosis is well established
- Measures of skills demand, skills supply, and skills mismatches abundant
- Forecasting established / foresight is fast developing
- Winners and losers identified
- Methodologies for measuring skills firmly in place…
- … NLP increasing the capacity to identify skill demands in real time…
- … but there is still plenty of space for skills surveys
- Evidence base is developing at pace

What is missing?

- Lack of local labour market data – the level at which people search for jobs
- Lack of balance – either really detailed (granular data) or highly aggregated data. This may not help provide people with skills to sustain them in the labour market
- Granular data tends to focus on generic / transversal skills
- Labour shortages versus skill shortages remains difficult to resolve
- Lots of data on individual perspectives on skill mismatches at the European level, but less so the employer one
- The wage dimension – especially at the EU level – is sometimes missing
- Labour market transitions over the lifecourse
- Emphasis on transferable skills – because easier to classify or ask questions about?
- Increasingly heavy reliance on scraped data at the expense of representative survey data
- Links between skills and economic development (especially at the local level)
- Uncertainty overplayed – but perhaps need to develop views of alternative futures
- Not clear how skills anticipation data being used especially by end users – employers, learners / students, curriculum developers – rather than intermediaries
- Conversion of demand side data into supply side actions not clear – is this a data or a communication problem?

For more information

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