The empirics of technology, employment and occupations: lessons learned and challenges ahead

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Outline

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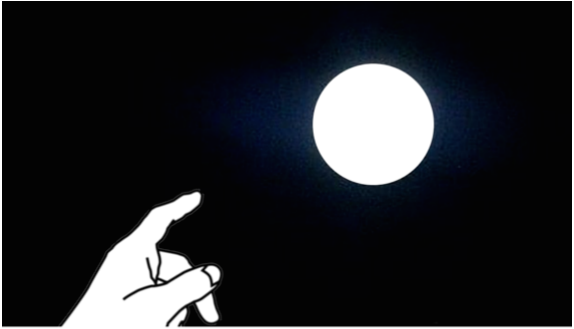
The problem of the finger and the moon

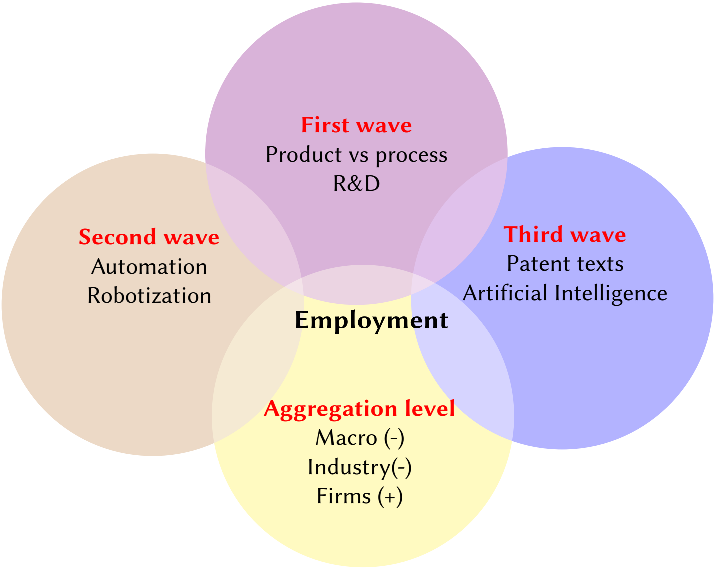


Scope of the paper

RQ: What has been learnt from recent debate and analysis regarding the threat that new technological transformation poses to the future of work?

- This paper is a critical review of the empirical literature resulting from recent years of debate and analysis regarding technology and employment and the future of work as threatened by technology, outlining both lessons learned and challenges ahead.
- We distinguish three waves of studies, and relate their heterogeneous findings to the choice of technological proxies, the level of aggregation, the adopted research methodology and to the relative focus on robots, automation and AI.

Three waves of innovation studies: technology and employment



Outline

The first wave - the role of product vs. process innovation along different levels of aggregation

- Macroeconomic studies
  - At the macroeconomic level, the labour-saving impact of new technologies should be compared with the possible counterbalancing effects of various market compensation mechanisms (Freeman et al. (1982), classical, neoclassical, or Keynesian nature)
  - Pros: an ideal setting for fully investigating the link between technology and employment, considering jointly the direct effects of process and product innovation, and all the indirect income and price compensation mechanisms.
  - Cons: problems in measuring aggregate technological change, the analytical complexity in identify the comp. mech. due to composition effects

The first wave - the role of product vs. process innovation along different levels of aggregation

- Sectoral studies
  - Product innovation, new sectors and structural change: manufacturing vs services
  - Positioning of sectors in the production chain (upstreamness versus downstreamness)
- Firm-level studies
  - since the late '90s studies have taken full advantage of newly available longitudinal datasets and have applied panel data econometric methodologies that take the time dimension and individual variability into account jointly.
  - attention in product versus process innovation (CIS) and use of R&D variables

The first wave - Results

- Firm-level
  - job-creating impact of innovation is small in magnitude and generally limited to high-tech and upstream sectors, characterised by higher R&D intensity, and by the prevalence of product innovation.
  - technological change embodied in process innovation may generate technological unemployment, particularly in downstream and more traditional sectors.
- Sectoral level
  - positive effect of technical change on employment is stronger in the knowledge-intensive service sector and in high tech manufacturing industries.
  - both R&D activities in manufacturing and the creation of new services (or new ways of providing old services) have a positive effect on employment dynamics.
- Macroeconomic level
  - The effect is however heterogeneous, depending on the characteristics both of markets and of the institutional framework.
  - Innovation is more likely to enhance employment where the compensation effect in terms of price decrease is more pronounced and where product innovation is more frequent (relative to process innovation).

The second wave - the revival of robots and automation

- Macroeconomic/sectoral level
  - based on IFR dataset, O*NET and PIAAC
  - mostly negative effects
  - robots and automation target middle and low skilled occupations

The second wave - the revival of robots and automation

- Firm-level studies
  - huge variety in the measuring of robot adoption (capital equipment, expenditure in energy, dummy variables,)
  - emerging evidence of between-industry and even within-industry heterogeneity: robot are not equally adopted
  - mixed results, mostly confirming positive effects, however papers lack of time comparability and are very country-specific

The third wave - patent text content and artificial intelligence

- The first group of studies involves analysis of the direct impact of AI on jobs, typically by the use of data on job posts or patents to assess AI exposure and study the impact of AI on employment.
  - work is at a very preliminary stage
  - results show that white-collar workers and knowledge workers could be relatively more affected
  - quality rather than the quantity of work

The third wave - patent text content and artificial intelligence

- The second group of studies involves using patent texts to analyse the proximity between specific innovation functions and occupations and tasks in the labour market.
- The authors of these studies argue that the language used in patent texts can be used to identify the tasks and skills that are exposed to automation.

Outline

Existing literature (cont'd)

Webb (2020) proposes a direct measure of exposure via co-occurrence of verb-noun pairs in the title of AI patents and O*NET tasks

Felten et al. (2021) links the Electronic Frontier Foundation dataset with O*NET abilities

Acemoglu et al. (2020) looks at AI exposed establishments (Webb, 2020, Felten et al., 2021) and their job posts using Burning Glass Technologies data

Meindl et al. (2021) matches the patent text corpus with the O*NET detailed work activities

Kogan et al. (2021) constructs a text-similarity measure between a corpus of breakthrough innovations (Kelly et al., 2018) and the Dictionary of Occupation Titles (DOT)

Objective of the paper - *Montobbio et al. 2023, The World Economy*, forthcoming

- build a *direct* measure of occupational exposure to labour-saving technologies
- 3-fold analysis
  1. labour-market (employment and wage)
  2. sectoral
  3. geographic

- to study the machine-task relationship we need to look at functions and operations of both machines, in relation to humans, and humans themselves
- functions and operations are better described in CPC definitions than in patents full-text
- tasks executed by humans are well described in the O*NET questionnaire
- technological classification codes allow us to pinpoint truly labour-saving tasks

Our starting point

Montobbio et al. (2022)[1] identify labour-saving patents among USPTO robotic applications (2009–2018)

1. robotics patents identified by CPC and keyword search (10 $\times$ `‘robots’`)
2. labour-saving patents identified by text query $\longrightarrow$ and manual validation (no false positives)

- 1,276 *truly* labour-saving patents

$$\underbrace{\begin{bmatrix} \textit{‘reduc’} \\ \textit{‘replac’} \\ \textit{‘elimin’} \\ \textit{‘save’} \\ \textit{‘lower’} \\ \textit{‘substitut’} \\ \textit{‘autom’} \end{bmatrix}}_{\text{verbal predicate}} \times \underbrace{\begin{bmatrix} \textit{‘labor’} \\ \textit{‘worker’} \\ \textit{‘human’} \\ \textit{‘employe’} \\ \textit{‘manpow’} \\ \textit{‘job’} \end{bmatrix}}_{\text{direct object}} \times \underbrace{\begin{bmatrix} \textit{‘cost’} \\ \textit{‘expenditure’} \\ \textit{‘expens’} \\ \textit{‘hour’} \\ \textit{‘intens’} \\ \textit{‘task’} \\ \textit{‘time’} \\ \textit{‘skill’} \end{bmatrix}}_{\text{object attribute}}$$

[1] Montobbio, F., J. Staccioli, M. E. Virgillito, and M. Vivarelli (2022) “Robots and the origin of their labour-saving impact”. *Technological Forecasting and Social Change* 174, 121122. DOI: `10.1016/j.techfore.2021.121122`

Examples of labour-saving patents

"Automated systems, such as robotic systems, are used in a variety of industries to ***reduce labo[u]r costs and/or increase productivity****. Additionally, the use of human operators can involve increased cost relative to automated systems."* [US20170178485A1]

"The use of [robotic] technology results in improved management of information, services, and data, increased efficiency, significant reduction of time, ***decreased manpower requirements****, and substantial cost savings."* [US20100223134A1]

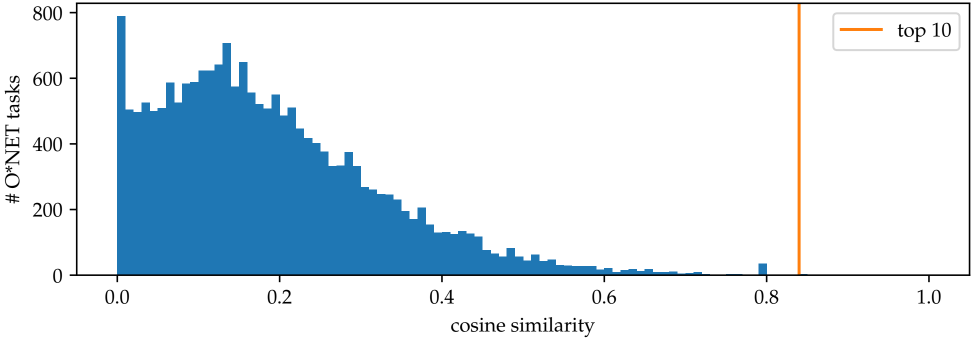
Cosine similarity (cont'd)

OCCUPATION	11-1011.00			...	53-7121.00		
TASK	8823	8824	...	...	...	12809	12810
CPC							
A01B	cos(A01B,8823)	cos(A01B,8824)	...	...	...	cos(A01B,12809)	cos(A01B,12810)
A01D	cos(A01D,8823)	cos(A01D,8824)	...	...	...	cos(A01D,12809)	cos(A01D,12810)
...	...	...	...	...	...	...	...
H05H	cos(H05H,8823)	cos(H05H,8824)	...	...	...	cos(H05H,12809)	cos(H05H,12810)
H05K	cos(H05K,8823)	cos(H05K,8824)	...	...	...	cos(H05K,12809)	cos(H05K,12810)

4. weigh by CPC frequency in LS patents[2]
5. sum across CPCs, and rescale between [0,1]

[2] codes B25*, G01*, G05*, G06*, and Y* are excluded because too general

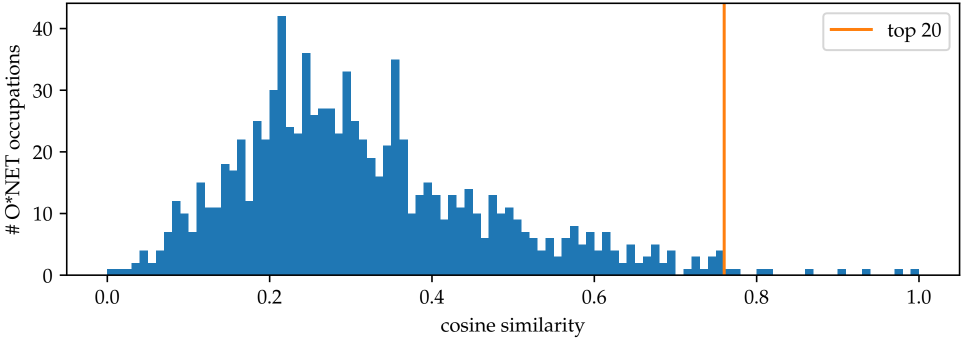
Tasks by similarity



Top tasks by similarity

#	Code	Description	CS
1	14587	Load materials and products into machines and equipment, or onto conveyors, using hand tools and moving devices	1.0
2	3202	Move levers or controls that operate lifting devices, such as forklifts, lift beams with swivel-hooks, hoists, or elevating platforms, to load, unload, transport, or stack material	0.96
3	3203	Position lifting devices under, over, or around loaded pallets, skids, or boxes and secure material or products for transport to designated areas	0.9
4	17928	Lift and move loads, using cranes, hoists, and rigging, to install or repair hydroelectric system equipment or infrastructure	0.89
5	15266	Manually or mechanically load or unload materials from pallets, skids, platforms, cars, lifting devices, or other transport vehicles	0.88
6	14584	Remove materials and products from machines and equipment, and place them in boxes, trucks or conveyors, using hand tools and moving devices	0.86
7	11839	Transport machine parts, tools, equipment, and other material between work areas and storage, using cranes, hoists, or dollies	0.85
8	3217	Load materials and products into package processing equipment	0.85
9	12805	Operate conveyors and equipment to transfer grain or other materials from transportation vehicles	0.85
10	12323	Communicate with systems operators to regulate and coordinate line voltages and transmission loads and frequencies	0.84

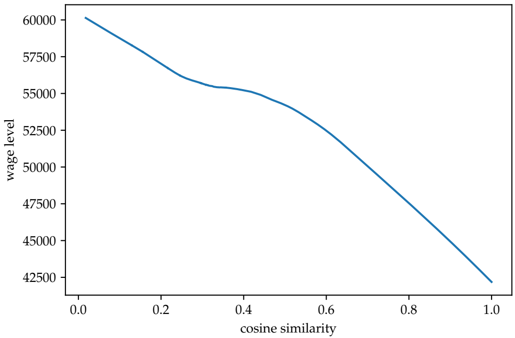
Occupations by similarity

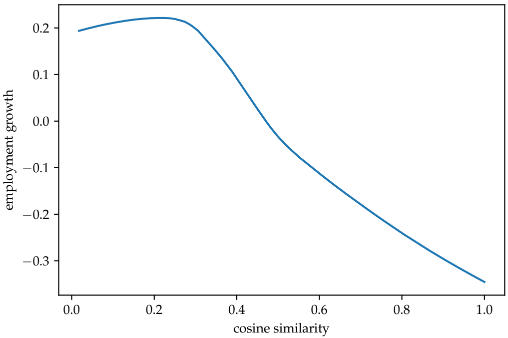


Top occupations by similarity

#	Code	Title	CS
1	53-7051.00	Industrial Truck and Tractor Operators	1.0
2	49-9043.00	Maintenance Workers, Machinery	0.97
3	53-7063.00	Machine Feeders and Offbearers	0.94
4	53-7064.00	Packers and Packagers, Hand	0.91
5	49-2091.00	Avionics Technicians	0.87
6	51-9111.00	Packaging and Filling Machine Operators and Tenders	0.81
7	49-3041.00	Farm Equipment Mechanics and Service Technicians	0.81
8	49-3092.00	Recreational Vehicle Service Technicians	0.78
9	49-3042.00	Mobile Heavy Equipment Mechanics, Except Engines	0.77
10	47-2111.00	Electricians	0.76
11	49-9098.00	Helpers–Installation, Maintenance, and Repair Workers	0.75
12	49-9041.00	Industrial Machinery Mechanics	0.75
13	51-9082.00	Medical Appliance Technicians	0.75
14	47-3011.00	Helpers–Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	0.75
15	51-9191.00	Adhesive Bonding Machine Operators and Tenders	0.75
16	51-9023.00	Mixing and Blending Machine Setters, Operators, and Tenders	0.74
17	13-1032.00	Insurance Appraisers, Auto Damage	0.73
18	51-4111.00	Tool and Die Makers	0.73
19	49-9081.00	Wind Turbine Service Technicians	0.72
20	51-8013.04	Hydroelectric Plant Technicians	0.72

Wage levels and employment growth





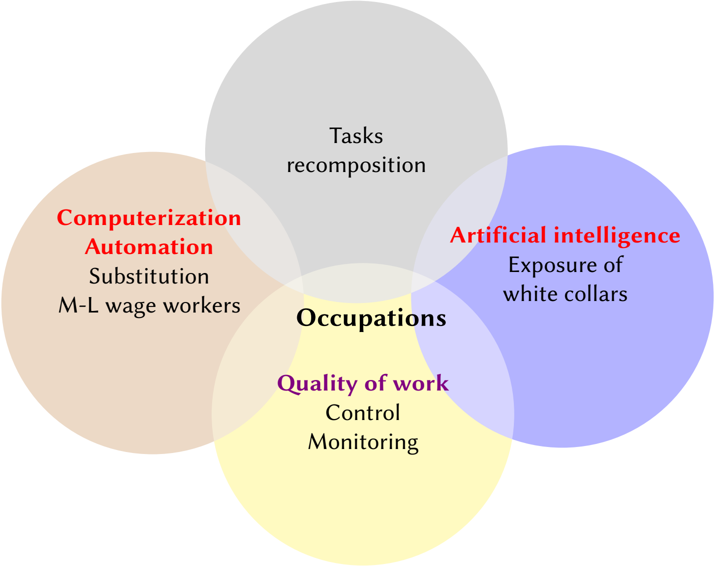
- robust LOWESS estimates of the underlying scatter plots (bandwidth = 0.8)

Summary of the results

- the cosine similarity matrix is overall very *sparse*
  - skewed distributions in both tasks and occupations
  - high similarity is a **rare event** (low probability of false positives)
- considering the top decile of the similarity distribution, around 8.6% of employees (≈12.6m) are exposed to substitution
- exposure to substitution is monotonically decreasing in wage: no U-shaped pattern but rather a negative declining relationship
- most affected occupations (2-digit) include "transportation and material moving" (logistics), "installation, maintenance, and repair" (automotive), "food preparation and serving"
- exposure to substitution is decreasing in employment growth: innovative efforts towards the weakest and cheapest segment of the labour market

Outline

Lessons learned and challenges ahead



Challenges ahead

- There are currently many alternative proxies for technology at different levels of aggregation: ex-ante biases
  - On the one hand, some technological variables, such as R&D expenditures and patents, are more linked to product innovation and often drive an overall positive employment impact (complementarity).
  - On the other hand, other technological variables, such as scrapping or robot adoption, are more related to process innovation, often involving an overall labour-saving employment impact.
- limitations and trade-offs affect the available empirical/econometric analysis
  - On the one hand, the relationship between technological change and employment triggers both partial equilibrium re-adjustments and general equilibrium compensation forces which are particularly difficult to disentangle in empirical analyses.
  - However, while microeconometric studies appear to be extremely precise in grasping the nature of innovation and in distilling information from very large datasets, they inevitably lose in terms of assessing the overall employment impact of technological change.

Challenges ahead

- limited degree of granularity in dealing with different technologies.
  - A finer analysis of the relationship between specific technological advancements, tasks, and skills becomes necessary for a detailed understanding of the impact on skills, the nature of job reallocation, the degree of obsolescence of tasks, and the possibility to learn on the job.
  - A more granular measurement of technologies is also required to design appropriate policy interventions affecting skill supply, labour market institutions and government policies, such as taxes, R&D subsidies, and regional policies for innovative clusters.
- the narrow focus on robotisation by the recent empirical literature should be seen as a further shortcoming.
  - At the very least, future analyses should encompass the entire AI domain AIWM technologies

Challenges ahead

- a major challenge for future research in this area should be to address the impact of technological transformation on labour quality, not only in terms of wages but also in terms of types of jobs and working conditions.
  - the aggregate quantitative employment impact of different forms of technological change (from robots to AI) is still unclear
  - what is becoming increasingly evident is that technology transforms how, and under what conditions, workers do their jobs.
  - the analysis of technological organisational capabilities at the workplace level (and their impact on the way technology is implemented and on the nature of the work process) and the institutional setting (e.g. trade unions and labour market regulations) are particularly promising and interesting avenues for research.

Outline

Conclusions

- The technology-employment nexus is a very important channel of transformation in labour markets and remains at the core of political economy, but it is not the only one and, possibly, not the most important.
- For example, the COVID-19 pandemic produced a massive drop in hours worked and deeply affected employment, unemployment and participation rates, as well as inequality and reorganisation of working activity on a global scale (ILO, 2022).
- The combined results of demand patterns and technological change lead different industries to react to new technologies in different ways, and this suggests potential disruptive changes for workers, as certain industries flourish while others decline.

Conclusions

- This paper makes the case that new productivity-improving technology will probably result in a substantial reallocation of labour, regardless of the overall impact.
- For this reason, it is important to understand how technology affects the organisation of the productive process and the way work is executed. The new waves of technological change are transforming the nature of work and the tasks required within the different types of occupations.
- The pace and scope of change in the automation process may be faster than previous automation waves, and also extend to white-collar and professional tasks.
- In tracing these effects, economists need accurate data to develop fine-grained proxies for technology, able to capture the impact of different trajectories such as, for example, automation, digitisation, and more standard ICT processes.