The Employment Impact of Emerging Digital Technologies

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Emerging Digital Technologies Shape the Future of Work

- The past decade has seen rapid advancements in digital (automation) technologies
  - Networking (5G, IoT, Swarm), Robotic navigation and control (self-driving cars, Cobots), Enhanced UI (AR/VR, virtual assistants), Additive Manufacturing, Artificial Intelligence (AI), Data Management and Security (blockchain).
- Extensive literature examines the employment impact of established digital technologies
  - Narrowly target specific technologies—often limited to particular applications of robots and AI (Felten et al. 2018, 2021; Webb 2019; Alekseeva et al. 2021; Acemoglu et al. 2022)
  - Or aggregate diverse technologies into broad automation indices (Mann and Püttmann 2023; Autor et al. 2024; Kogan et al. 2024)
- Little is known about the employment impact of this diverse array of emerging digital technologies
  - Net employment outcome depends on the balance between automation and augmentation (Acemoglu and Restrepo 2018)
  - Many digital technologies exhibit complementarities – simultaneous adoption (e.g., cloud storage and cloud computing)

This paper

1. We estimate the exposure of industries and occupations to 40 EDT
   - Novel, systematic, and scalable approach using sentence transformer models
   - Technological relevance for industries (3-digits) and *occupations* (4-digits) based on semantic similarity between patent descriptions and international classifications
2. IV shift-share framework to estimate the employment effects of EDT across European regions from 2012 to 2019
   - Explicitly accounting for complementarities among technologies
3. We classify technologies into labor-saving, labor-neutral, and labor-augmenting
   - We identify distinct patterns of effects across different skill groups
   - We rationalize these empirical findings within a task-based theoretical framework

Main results

1. High-educated occupations (i.e. managers, professionals, and technicians) are among the most exposed, alongside mid-educated occupations (i.e. machine operators and clerks)
2. Overall positive impact of emerging digital technologies on regional employment rate
   - 1-SD increase in regional exposure $\Longrightarrow$ 0.91 pp. ($\approx$ 1.8%) increase in the emp-to-pop. ratio
   - $\uparrow$ low- & high-educated and $\downarrow$ mid-educated employment
3. Significant heterogeneity in the impact of individual technologies and applications
   - Labor-saving displace low- and middle-educated employment by automating simpler tasks, creating tasks for high-educated (e.g. robots, ML, electronic messaging, mobile payment)
   - Labor-augmenting increase productivity and enable low- and middle-educated workers to perform increasingly complex tasks (e.g. 3D printing, remote monitoring, and e-learning)

Contributions

- Labor market impact of automation technologies (Arntz et al. 2017; Frey and Osborne 2017; Graetz and Michaels 2018; Acemoglu and Restrepo 2019; Jerbashian 2019; Webb 2019; Acemoglu and Restrepo 2020; Vries et al. 2020; Dauth et al. 2021; Aghion et al. 2022; Acemoglu et al. 2022; Graetz et al. 2022; Mann and Püttmann 2023; Adachi et al. 2024; Autor et al. 2024)
  - Different impacts of (potentially complementary) 40 emerging digital technologies
  - Specific technologies may negatively impact employment (e.g., robots, AI) when analyzed in isolation, but their aggregate effect becomes positive when considered altogether
- Technology-skill complementarity (Goldin and Katz 1998; Autor et al. 2003, 2006; Goos et al. 2009; Autor and Dorn 2013; Goos et al. 2014; Kogan et al. 2024)
  - Estimate which technology substitutes or complements different skills
- Exposure to technology (Frey and Osborne 2017; Kelly et al. 2021; Felten et al. 2021; Jurkat et al. 2022; Felten et al. 2023; Mann and Püttmann 2023; Dechezleprêtre et al. 2023; Autor et al. 2024)
  - Novel scalable methodology using sentence transformers
  - Unique open access metric constructed at a granular level using international standard classifications covering a broad spectrum of digital technologies

Outline

Outline

Identifying Emerging Digital Technologies from Patents

- We use 190,714 patents identified in Chaturvedi et al. (2023) as the emerging core of digital technologies related to automation $p \in \mathcal{P}$
  - Filed between 2012 and 2021 (extracted from Derwent Database) (▸ Patent content)

- We produce embeddings of patent titles (Emb_p) with a pre-trained sentence transformer MPNet v2 (Song et al. 2020) (▸ Titles)
  - Masked and Permuted Pre-training for Language Understanding: Trained on 1B sentence pairs from diverse domains (academic papers, Wikipedia, Reddit comments, Stack Exchange, etc): understand the context of both technologies and their applications
  - Map patent text to a 768-dimensional vector space by creating a single vector of embeddings for each patent

- We cluster patents into 40 core emerging digital technologies using k-means based on the proximity of their vectors of embeddings, i.e. $p \in \mathcal{P}_k$ where $k \in [1, 40]$

9 Technology Families: 40 Emerging Technologies

▸ Distribution ▸ Co-occurrence

	Family		Emerging Digital Technology
F1	**3D Printing**	01	3D Printer Hardware
		02	3D Printing
		03	Additive Manufacturing
F2	**Embedded Systems**	04	Smart Agriculture & Water Management
		05	Internet of Things (IoT)
		06	Predictive Energy Management and Distribution
		07	Industrial Automation & Robot Control
		08	Remote Monitoring & Control Systems
		09	Smart Home & Intelligent Household Control
F3	**Smart Mobility**	10	Intelligent Logistics
		11	Autonomous Vehicles & UAVs
		12	Parking and Vehicle Space Management
		13	Vehicle Telematics & Electric Vehicle Management
		14	Passenger Transportation
F4	**Food Services**	15	Food Ordering & Vending Systems
F5	**E-Commerce**	16	Digital Advertising
		17	Electronic Trading and Auctions
		18	Online Shopping Platforms
		19	E-Coupons & Promotion Management

	Family		Emerging Digital Technology
F6	**Payment Systems**	20	Electronic Payments & Financial Transactions
		21	Mobile Payments
		22	Gaming & Wagering Systems
F7	**Digital Services**	23	Digital Authentication
		24	E-Learning
		25	Location-Based Services & Tracking
		26	Voice Communication
		27	Electronic Messaging
		28	Workflow Management
		29	Cloud Storage & Data Security
		30	Information Processing
		31	Cloud Computing
		32	Recommender Systems
		33	Social Networking & Media Platforms
		34	Digital Media Content
F8	**Computer Vision**	35	Augmented and Virtual Reality (AR/VR)
		36	Machine Learning & Neural Networks
		37	Medical Imaging & Image Processing
F9	**HealthTech**	38	Health Monitoring
		39	Medical Information
		40	E-Healthcare

Outline

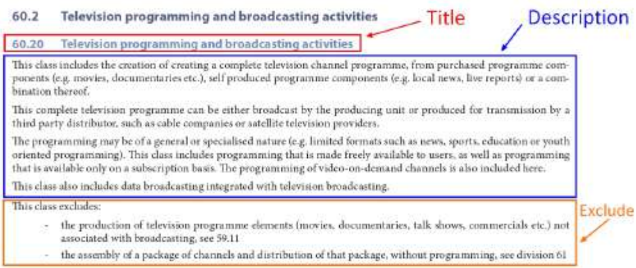
Exposure Scores for Industries: Summary

▸ Detailed proc.

- Derwent Patent: example **Targeted TV Advertising** patent, ID 2013B87254
  - Technology description: Method for targeting television advertisement based on profile linked to online device; Use/function: **, involves** selecting television advertisement to be directed to set-top box based on profile information pertaining to user or online activity
- NACE Rev.2 Classification Industry (3-digit): each industry has a title and a description

- We compute cosine similarities between industries and patents description and function
- We filter out irrelevant matches

⇒ We establish a (semantic) connection between an invention p and a set of relevant industries $i \in \mathcal{I}$


60.2 Television programming and broadcasting activities

60.20 Television programming and broadcasting activities

This class includes the creation of creating a complete television channel programme, from purchased programme components (e.g. movies, documentaries etc.), self produced programme components (e.g. local news, live reports) or a combination thereof.

This complete television programme can be either broadcast by the producing unit or produced for transmission by a third party distributor, such as cable companies or satellite television providers.

The programming may be of a general or specialised nature (e.g. limited formats such as news, sports, education or youth oriented programming). This class includes programming that is made freely available to users, as well as programming that is available only on a subscription basis. The programming of video-on-demand channels is also included here.

This class also includes data broadcasting integrated with television broadcasting.

This class excludes:

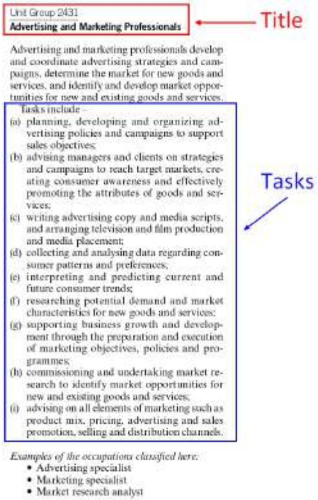
- the production of television programme elements (movies, documentaries, talk shows, commercials etc.) not associated with broadcasting, see 59.11
- the assembly of a package of channels and distribution of that package, without programming, see division 61

Cosine Similarity for Occupations: Summary

Detailed proc.

- We use the ISCO-08 Classification (at the 4-digit level)
  - Each occupation $o \in \mathcal{O}$ has a title and a list of tasks
- We compute cosine similarities between occupations and patents
- We filter out irrelevant matches

$\Rightarrow$ We establish a (semantic) connection between an invention p and a set of relevant occupations $o \in \mathcal{O}$


Unit Group 2431
Advertising and Marketing Professionals

Advertising and marketing professionals develop and coordinate advertising strategies and campaigns, determine the market for new goods and services, and identify and develop market opportunities for new and existing goods and services.

Tasks include –
(a) planning, developing and organizing advertising policies and campaigns to support sales objectives;
(b) advising managers and clients on strategies and campaigns to reach target markets, creating consumer awareness and effectively promoting the attributes of goods and services;
(c) writing advertising copy and media scripts, and arranging television and film production and media placement;
(d) collecting and analysing data regarding consumer patterns and preferences;
(e) interpreting and predicting current and future consumer trends;
(f) researching potential demand and market characteristics for new goods and services;
(g) supporting business growth and development through the preparation and execution of marketing objectives, policies and programmes;
(h) commissioning and undertaking market research to identify market opportunities for new and existing goods and services;
(i) advising on all elements of marketing such as product mix, pricing, advertising and sales promotion, selling and distribution channels.

Examples of the occupations classified here:
- Advertising specialist
- Marketing specialist
- Market research analyst

Aggregation to Technology: Exposure Scores

- We aggregate patent cosine similarity scores C_i^p and C_o^p to the technology level: C_i^k and C_o^k
  - Weighted sum based on the number of citations ▸ Weighting Scheme
  - IHS Normalization: $X_d^k = \sinh^{-1}\left(C_d^k\right)$, with $d = \{i, o\}$
  - Cumulative exposure for the period 2012–2021

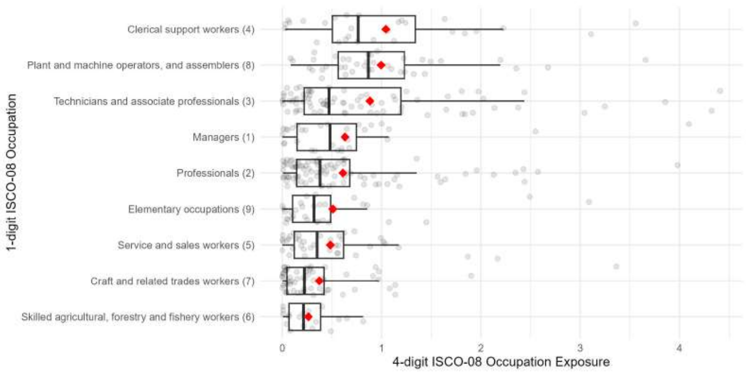
3-digit NACE	Industry Title (i)	Digital Technology (k)	X_i^k
28.2	Manufacturing of general-purpose machinery	3D Printer Hardware	8.79
28.9	Manufacturing of special-purpose machinery	3D Printer Hardware	8.53
64.1	Monetary intermediation	E-Payment	8.46
73.1	Advertising	Digital Advertising	8.39
82.9	Business support service	E-Payment	8.27

Interpreting Exposure Scores

- Indicate the relevance of a technology to an industry/occupation
  - Industries: integration of a technology into the production process and/or the output
  - Occupations: ability of a technology in performing tasks and functions inherent to the occupation
- Exposure per se does not describe the nature of the relationship between a technology and an industry/occupation
  - Do not discriminate user or producer status of an industry
  - Do not discriminate use for complementing or replacing tasks
  - Revealed through the impact – and what the technology can do
- They align with existing metrics in the literature (Frey and Osborne 2017; Webb 2019; Felten et al. 2021) ▸ Details
  - But, they also capture additional dimensions of these technologies: either due to the nonexistence or a narrower focus

Outline

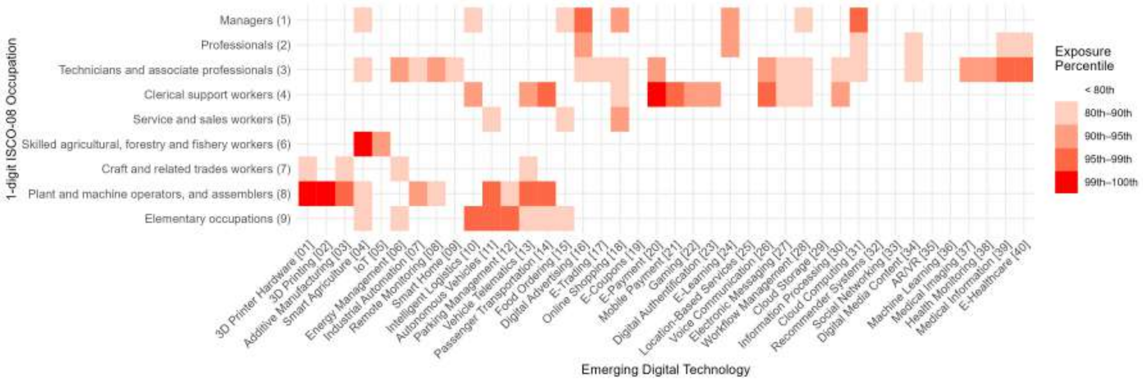
Occupation Exposure to all Technologies (1-digit)



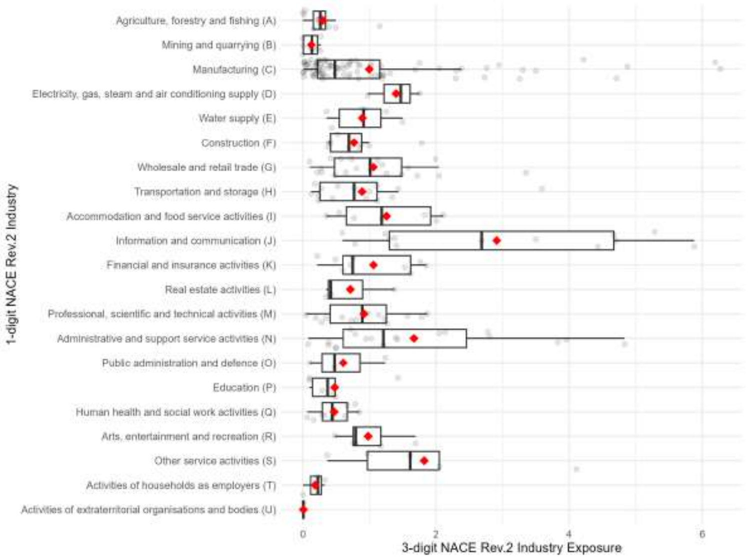
Code	ISCO Occupation	X_o	$CR3_o$
3513	Computer network and systems technicians	4.41	11.7
3511	ICT operations technicians	4.32	12.4
1330	ICT service managers	4.10	13.1
2523	Computer network professionals	3.98	12.7
3512	ICT user support technicians	3.86	12.4
8132	Photographic products machine operators	3.66	15.9
4223	Telephone switchboard operators	3.56	14.6
7422	ICT installers and servicers	3.36	14.3
3514	Web technicians	3.25	13.3
4132	Data entry clerks	3.11	15.6
9623	Meter readers and vending-machine collectors	3.09	16.9
3133	Chemical processing plant controllers	3.04	18.0
8322	Car, taxi and van drivers	2.68	21.8
2153	Telecommunications engineers	2.57	17.1
1324	Supply, distribution and related managers	2.55	19.8
9621	Messengers, package deliverers and luggage porters	2.49	19.7
2513	Web and multimedia developers	2.44	19.5
3311	Securities and finance dealers and brokers	2.44	22.7
2521	Database designers and administrators	2.43	17.8
3252	Medical records and health information technicians	2.38	25.3
8183	Packing, bottling and labelling machine operators	2.36	18.0
2622	Librarians and related information professionals	2.35	20.9
4323	Transport clerks	2.23	24.5
8312	Railway brake, signal and switch operators	2.20	21.0
5244	Contact centre salespersons	2.17	20.7
3522	Telecommunications engineering technicians	2.13	19.4
2529	Database and network professionals n.e.c.	2.13	20.7
3135	Metal production process controllers	2.03	20.2
3114	Electronics engineering technicians	1.98	19.7
2522	Systems administrators	1.96	17.6

Notes: This table presents the top 30 4-digit ISCO-08 occupations ranked by exposure to all emerging digital technologies. Columns (from left to right) correspond to occupation code, occupation title, average exposure to emerging digital technologies, top-3 concentration ratio which represents the sum of top-3 technology exposure shares (in percent).

Occupation Exposure to each Technology (1-digit)



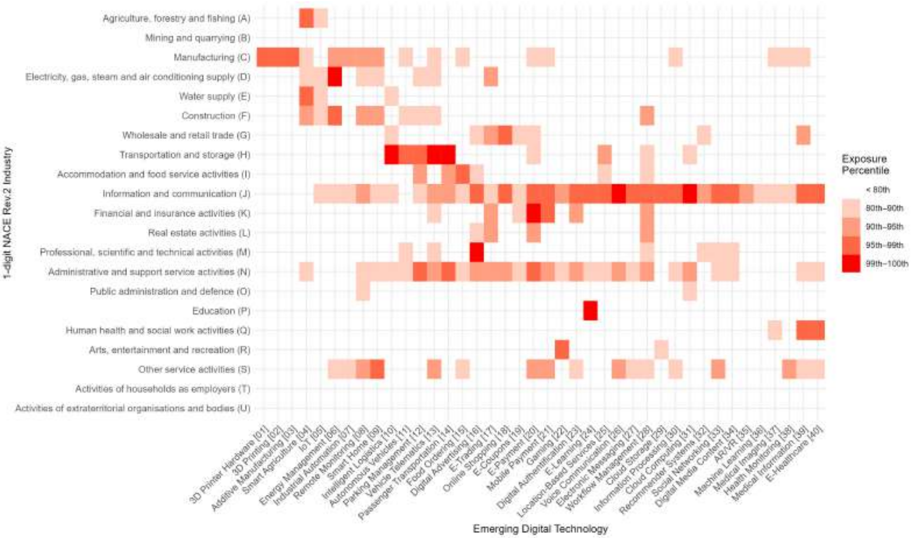
Industry Exposure to all Technologies (Sections)



Code	NACE Industry	X_i	$CR3_i$
26.3	Manufacture of communication equipment	6.28	9.7
26.2	Manufacture of computers and peripheral equipment	6.19	9.5
63.1	Data processing, hosting and related activities	5.88	10.0
62.0	Computer programming, consultancy and related activities	5.28	10.6
26.5	Manufacture of instruments and appliances for measuring	4.88	11.8
82.9	Business support service activities n.e.c.	4.83	11.5
28.2	Manufacture of other general-purpose machinery	4.71	12.7
63.9	Other information service activities	4.70	11.8
61.2	Wireless telecommunications activities	4.67	11.7
61.9	Other telecommunications activities	4.43	12.2
33.1	Repair of fabricated metal products, machinery and equipment	4.22	12.1
95.1	Repair of computers and communication equipment	4.11	12.2
79.9	Other reservation service and related activities	3.96	13.4
80.2	Security systems service activities	3.83	14.2
52.2	Support activities for transportation	3.59	16.0
27.9	Manufacture of other electrical equipment	3.50	15.1
61.1	Wired telecommunications activities	3.50	13.8
47.4	Retail sale of information and communication equipment	3.35	15.2
26.4	Manufacture of consumer electronics	3.30	13.1
28.9	Manufacture of other special-purpose machinery	3.26	18.3
27.1	Manufacture of electric motors, generators and transformers	2.95	18.3
82.2	Activities of call centres	2.81	16.2
80.1	Private security activities	2.78	16.6
26.1	Manufacture of electronic components and boards	2.76	16.8
17.2	Manufacture of articles of paper and paperboard	2.73	14.8
58.1	Publishing of books, periodicals and other publishing activities	2.69	17.4
27.3	Manufacture of wiring and wiring devices	2.38	17.7
18.2	Reproduction of recorded media	2.31	20.0
33.2	Installation of industrial machinery and equipment	2.30	20.6
82.1	Office administrative and support activities	2.14	18.8

Notes: This table presents the top 30 3-digit NACE Rev.2 industries ranked by exposure to all emerging digital technologies. Columns (from left to right) correspond to industry code, industry title, average exposure to emerging digital technologies, top-3 concentration ratio which represents the sum of top-3 technology exposure shares (in percent).

Industry Exposure to each Technology (Sections)



Outline

Effect of Technological Change on Employment

We estimate the following empirical specification:

$$\Delta Y_r = \alpha + \beta X_r + Z\delta + \phi_{c(r)} + u_r$$

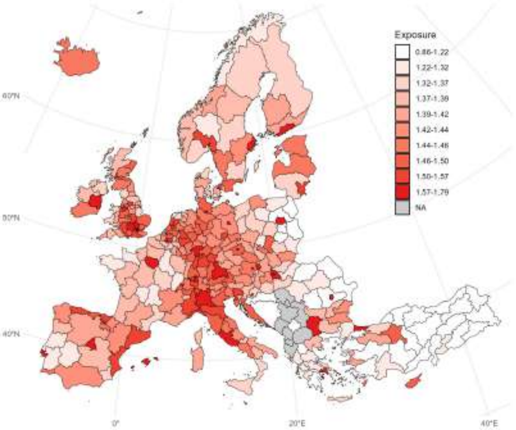
where

- ΔY_r is the change in the regional $\frac{Employment}{population}$ 2012-2019 (in pp.)
- X_r is the regional exposure to emerging digital technologies
- Z is a set of covariates, $\phi_{c(r)}$ are country FE, and u_r the error term

- Labour data: Regional European Labour Force Survey (EU-LFS)
  - Sample: 320 NUTS-2 European regions from 32 European countries
  - Employment in 10 *broad* sectors of activities: groups of 1–digit NACE industries
  - Demographic controls
- Exposure: TechXposure Database – cumulative exposure scores 2012-2019 by sector

Shift-Share Regional Exposure

- Regional Exposure: $X_r = \sum_j l_{rj} X_j$,
  - l_{rj} is the emp. share of sector j in region r (2010)
  - X_j is the average exposure of sector j to *all* emerging digital technologies (2012–2019)
- Identifying assumption: Sectoral exposure X_j is quasi-exogenous to changes in regional employment within Europe
  - Only 7.1% of EU patents
- We recalculate X_r after excluding European patents to instrument the regional exposure



Overall Impact of Emerging Digital Technologies on Regional Employment

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) × 100				
	Weighted				Unweighted
	(1)	(2)	(3)	(4)	(5)
Exposure (Standardized)	0.641**	0.913***	0.963***	1.140***	0.739***
	(0.241)	(0.139)	(0.129)	(0.134)	(0.145)
Country FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry share			✓	✓	✓
Exclude Top 10% Exposed Regions				✓	
R^2	0.668	0.697	0.697	0.707	0.721
Adj. R^2	0.629	0.654	0.653	0.660	0.681
Num. obs.	320	320	320	288	320

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019). Regressions are weighted by population in 2010. Column (1) includes country fixed effects; Column (2) adds demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, and the proportions of the population with secondary and tertiary education levels; Column (3) adds the share of employment in the industry sector.

Impact by Demographic Group and Education

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) × 100							
	All	Gender		Age		Skill		
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (Standardized)	0.913***	0.626***	0.287***	0.139***	0.775***	0.527*	−0.297***	0.704***
	(0.139)	(0.118)	(0.031)	(0.027)	(0.119)	(0.240)	(0.066)	(0.129)
Emp-to-pop. Ratio in 2012	50.14	22.22	27.92	4.76	45.38	11.89	23.11	15.00
Change (in %)	1.83	2.83	1.03	2.94	1.72	4.46	−1.29	4.71
R^2	0.697	0.557	0.725	0.329	0.722	0.623	0.750	0.647
Adj. R^2	0.654	0.496	0.686	0.236	0.683	0.571	0.715	0.598
Num. obs.	320	320	320	320	320	320	320	320

Notes:$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019). Regressions are weighted by population in 2010. Demographics (in 2010) include sum of exposure shares; country fixed effects; demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, the proportions of the population with secondary and tertiary education levels.

Placebo Estimate for the Pre-Period (2002–2009)

	Dep. var: Δ Emp-to-pop. Ratio (2002-2009) $\times$ 100							
	All	Gender		Age		Skill		
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (Standardized)	−0.176	−0.067	−0.109	−0.010	−0.175	−0.042	−0.089	0.318*
	(0.263)	(0.145)	(0.162)	(0.102)	(0.244)	(0.193)	(0.196)	(0.186)
Emp-to-pop. Ratio in 2012	50.93	22.25	28.69	5.70	45.23	14.22	24.52	11.39
Change (in %)	−0.35	−0.30	−0.38	−0.17	−0.39	−0.29	−0.36	2.79
R^2	0.713	0.709	0.766	0.676	0.692	0.747	0.767	0.625
Adj. R^2	0.667	0.663	0.729	0.625	0.643	0.708	0.731	0.565
Num. obs.	258	258	258	258	258	258	258	258

Notes:$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019). Regressions are weighted by population in 2010. Demographics (in 2010) include sum of exposure shares; country fixed effects; demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, the proportions of the population with secondary and tertiary education levels.

Outline

Individual Effects of Emerging Digital Technologies

- Regional exposure to a specific technology k:

$$X_r^k = \sum_j l_{rj} X_j^k$$

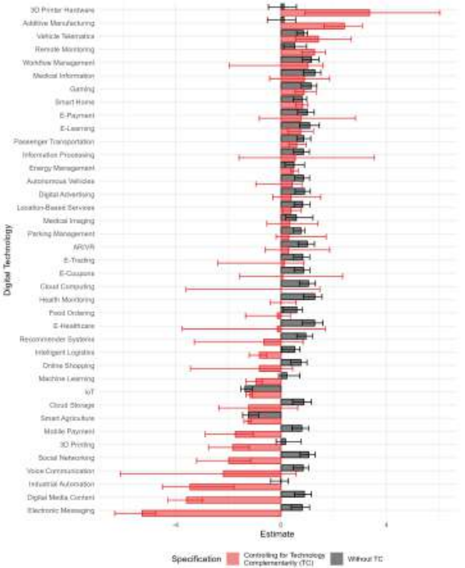
- Main challenge: technologies can complement eachother (e.g., robots and ICT)
  - More likely within the same technology family (e.g., cloud computing and cloud storage)

- Empirical model:

$$\Delta Y_r = \alpha + \beta_k X_r^k + \underbrace{\gamma_{1k} X_r^{K\setminus\{k\}}}_{\text{Within-Family Complementarity}} + \underbrace{\gamma_{2k} X_r^{-K}}_{\text{Between-Family Complementarity}} + Z\delta + \phi_{c(r)} + u_r,$$

  - X_r^k is the regional exposure to k
  - $X_r^{K\setminus\{k\}}$ is the regional exposure to all other technologies within the same family (excluding k)
  - X_r^k is the regional exposure to all remaining emerging digital technologies

- Accounting for complementarity between digital technologies is essential
  - Many of these technologies are deployed together
  - Failure to account for this joint adoption may bias estimates toward the average joint positive effect
- Digital technologies can be grouped into:
  - Labor-augmenting (e.g., E-Learning)
  - Labor-saving (e.g., Industrial Automation)
  - Labor-neutral (e.g., Autonomous Vehicles)

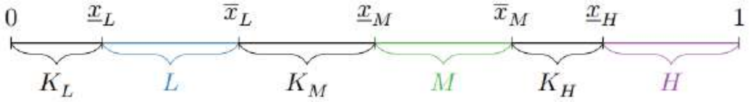


Outline

Outline

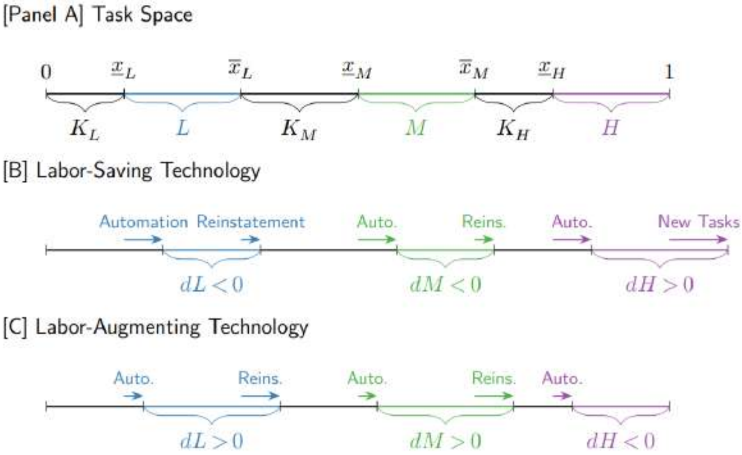
A Task-Based Model with Differentiated Input Factors

- The economy produces a final good by aggregating a continuum of tasks through a CES aggregator
- Three labor types $l \in \{L, M, H\}$ and three associated capital types $k \in \{K_L, K_M, K_H\}$
  - Each capital type performs the simpler tasks to routinise
  - Tasks are continuously distributed along an 'expertise' spectrum and assigned to factors based on their comparative advantage (Autor and Thompson 2025)
- The task space is endogenously segmented by the relative unit costs of factors

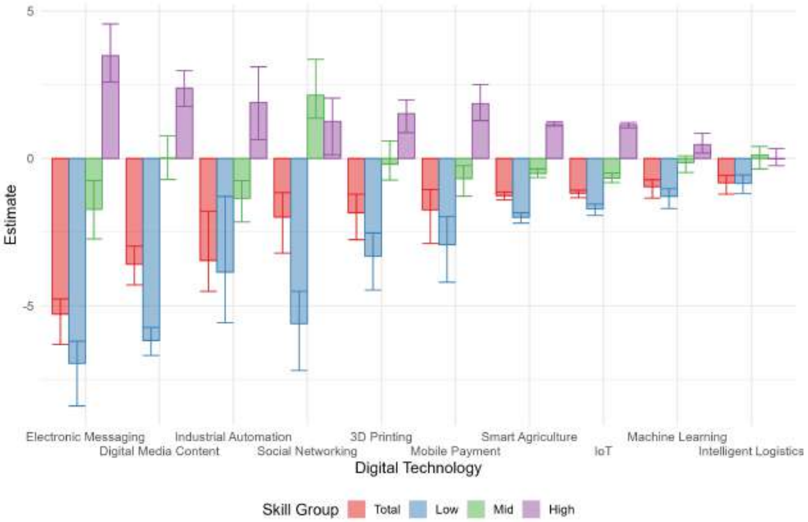


Introducing an Emerging Digital Technology (EDT)

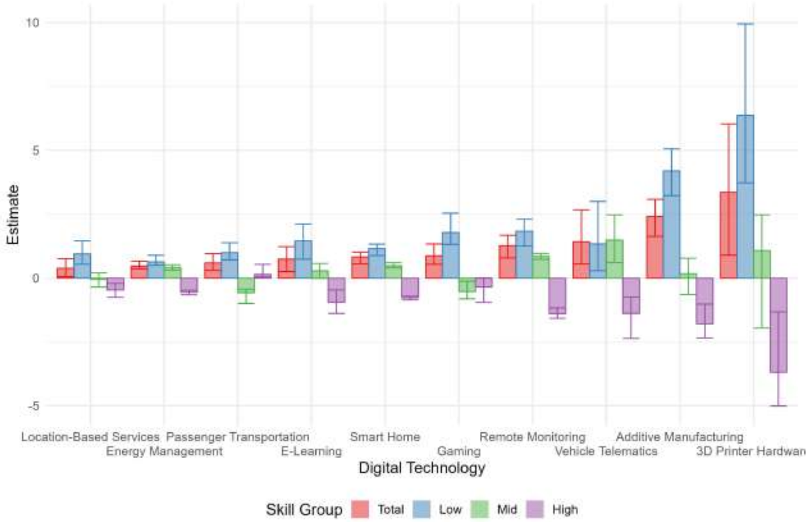
1. EDT substitute tasks easy to routinise;
2. creates new tasks, that require high skilled, e.g. to use EDT;
3. reshapes the allocation of existing tasks, by increasing factor-specific productivity and expertise which change relative unit costs



Employment Effects of Labor-Saving Digital Technologies by Skill Groups



Employment Effects of Compl. Digital Technologies by Skill Groups



Outline

Conclusion

- We measure the exposure of industries and occupations to 40 emerging digital technologies and estimate their impact on employment in European regions, explicitly accounting for their complementarity.

- Main takeaways:
  1. Professional and managerial occupations are among those most exposed
  2. Overall positive impact on employment, heterogeneous across workers (polarization)
     - Focusing solely on hype technologies like AI and robotics risks overlooking the broader, positive employment effects arising from interactions among diverse digital innovations
  3. Tech complementarity changes the impact of individual technologies
  4. Heterogeneity by technology
     - Labor-saving technologies lead to an automation of tasks carried on by low- and middle-educated workers, creating new tasks for high-educated
     - Labor-augmenting technologies augment expertise low- and middle-educated employment replacing the higher educated

Thank you for your attention

Comments most welcome

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- Exposure data available as open–access database:
  - github.com/FabienPetitEconomics/TechXposure
- Exposure at all aggregation levels
  - 4-digit ISCO-08 occupations and 3-digit NACE Rev.2 industries
  - 40 emerging digital technologies (from 9 technology families)

Some Examples of Patents

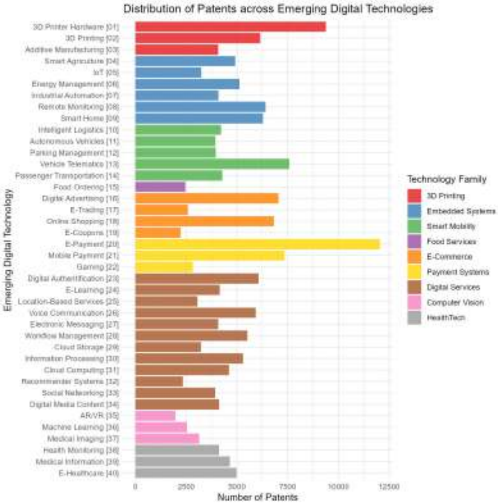
Go back

- Intelligent Vehicular Control Device (201713859U, 2017)
  - Vehicle intelligent logistics control device, **has** *GPS locating module for obtaining position information of transport vehicle through main control chip, RFID reader for reading RFID tag information, and 4G module connected with server*

- Speech Recognition System (202048118D, 2020)
  - System for recognizing training speech, **has** *process or which is configured to increment counter associated with word sequences, and train language model of automatic transcription system using word sequences and counter*

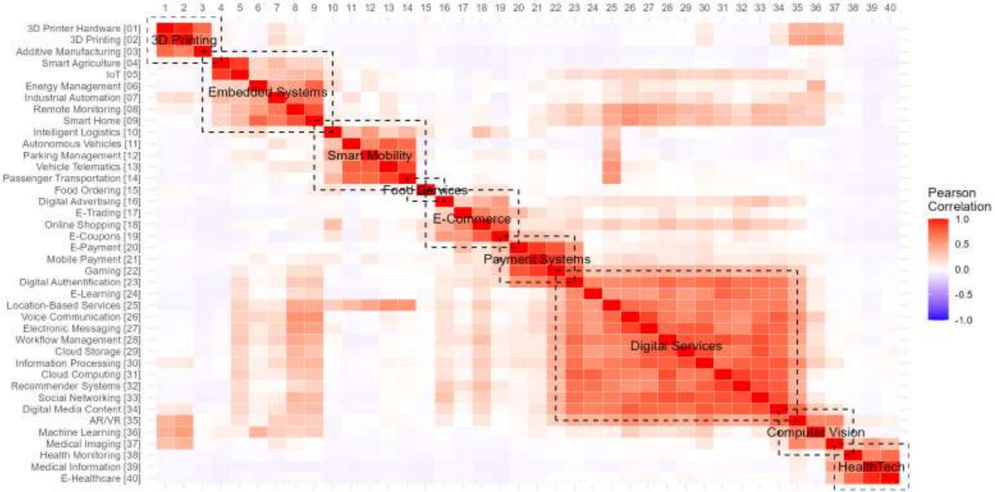
Distribution of Patents

Go back



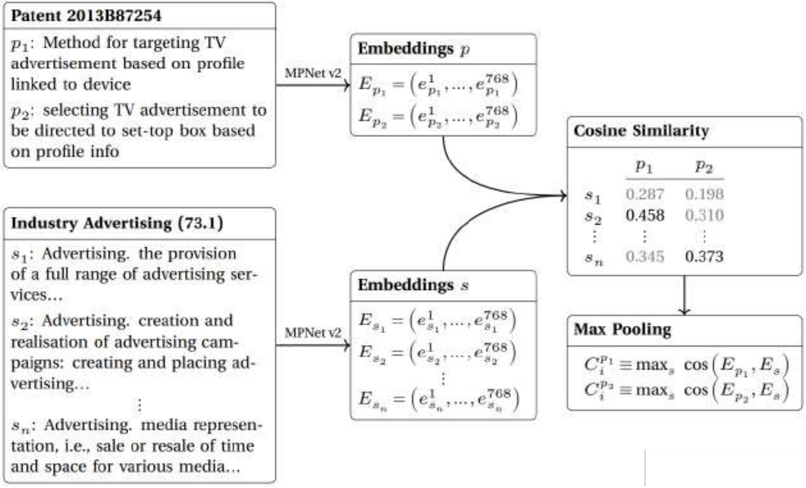
Semantic Co-Occurrence of Technologies in 3–digit ISCO-08

Go back



Semantic-Based Exposure: Patent Level Similarity

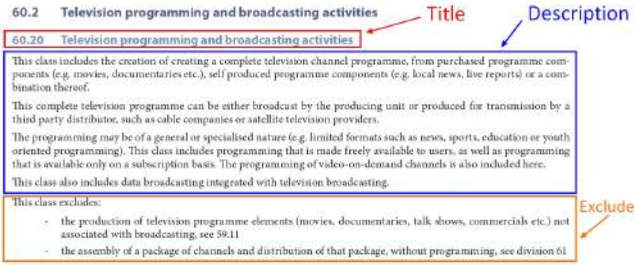
Go back



NACE Rev.2 Industry Classification (at the 3-digit level)

- Each industry $i \in \mathcal{I}$ has a title, a description, and exclusions

1. We break descriptions into individual sentences
2. We concatenate each sentence with its title
3. We represent these composite sentences as $s \in S_i$



60.2 Television programming and broadcasting activities

60.20 Television programming and broadcasting activities

This class includes the creation of creating a complete television channel programme, from purchased programme components (e.g. movies, documentaries etc.), self produced programme components (e.g. local news, live reports) or a combination thereof.

This complete television programme can be either broadcast by the producing unit or produced for transmission by a third party distributor, such as cable companies or satellite television providers.

The programming may be of a general or specialised nature (e.g. limited formats such as news, sports, education or youth oriented programming). This class includes programming that is made freely available to users, as well as programming that is available only on a subscription basis. The programming of video-on-demand channels is also included here.

This class also includes data broadcasting integrated with television broadcasting.

This class excludes:

- the production of television programme elements (movies, documentaries, talk shows, commercials etc.) not associated with broadcasting, see 59.11
- the assembly of a package of channels and distribution of that package, without programming, see division 61

- This results in 271 industries at the 3-digit level, each represented by 11 composite sentences on average

Embeddings and Cosine Similarity Scores

- We produce the embeddings of these composite sentences $Emb_{s,i}$ (with MPNet v2)
- For each patent $p \in \mathcal{P}$, we compute the cosine similarity with its description p_1 and its function p_2:

$$C^{p_1}_{s,i} = \frac{Emb_{s,i} \cdot Emb_{p_1}}{||Emb_{s,i}|| \; ||Emb_{p_1}||} \qquad \text{and} \qquad C^{p_2}_{s,i} = \frac{Emb_{s,i} \cdot Emb_{p_2}}{||Emb_{s,i}|| \; ||Emb_{p_2}||}$$

- For each (i, p_1) and (i, p_2) combinations, we retain the composite sentence s that exhibits the highest cosine similarity score:

$$C^{p_1}_{i} := \max_{s \in S_i} C^{p_1}_{s,i} \qquad \text{and} \qquad C^{p_2}_{i} := \max_{s \in S_i} C^{p_2}_{s,i}$$

Filtering with Redundancy

Go back

- For (i, p) combinations, we separately rank the sub-pairs (i, p_1) and (i, p_2) based on $C_i^{p_1}$ and $C_i^{p_2}$
- We identify relevant pairs $(i, p)^\star$ if both sub-pairs (i, p_1) and (i, p_2) are within the top 10 of their respective rankings
- For $(i, p)^\star$, we calculate the harmonic mean:

$$C_i^p = 2\left(\frac{1}{C_i^{p_1}} + \frac{1}{C_i^{p_2}}\right)^{-1}$$

Table: Example for Targeted TV Advertising

Code	NACE Industry	Cosine Similarity $C_i^{p_1}$	$C_i^{p_2}$	C_i^{p}
60.2	Television programming and broadcasting activities	0.391	0.445	0.416
73.1	Advertising	0.458	0.373	0.411
73.2	Market research and public opinion polling	0.295	0.272	0.283
59.1	Motion picture, video and television programme activities	0.271	0.263	0.267
61.2	Wireless telecommunications activities	0.290	0.229	0.256
26.3	Manufacture of communication equipment	0.257	0.240	0.249
78.1	Activities of employment placement agencies	0.265		
47.9	Retail trade not in stores, stalls or markets	0.263		
56.3	Beverage serving activities	0.261		
80.1	Private security activities	0.253		
61.3	Satellite telecommunications activities		0.294	
61.1	Wired telecommunications activities		0.237	
97.0	Activities of households as employers of domestic personnel		0.231	
58.1	Publishing of books, periodicals and other publishing activities		0.223	

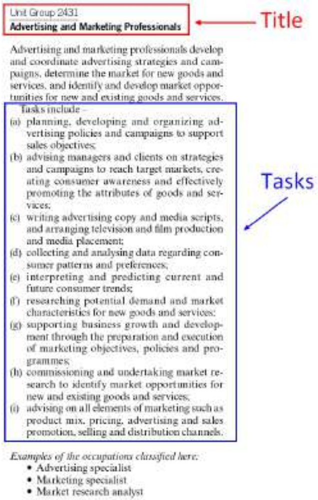
Notes: Patent description p_1 is "Method for targeting television advertisement based on profile linked to online device" (Column 3) and the function principle p_2 is "selecting television advertisement to be directed to set-top box based on profile information pertaining to the user or online activity" (Column 4). Industries are ranked according to Column 3 in decreasing order.

$\Rightarrow$ We establish a (semantic) connection between an invention p and a set of relevant industries $i \in \mathcal{I}$

Cosine Similarity for Occupations: Summary

- We use the ISCO-08 Classification (at the 4-digit level)
  - Each occupation $o \in \mathcal{O}$ has a title and a list of tasks
- We produce the embeddings of occupation title as Emb_{o_1} and of a task s as Emb_{s,o_2}
- We compute cosine similarities $C^p_{o_1}$ and $C^p_{o_2} := \arg\max_{s \in S_o} C^p_{s,o_2}$
- Same redundancy filtering and take the harmonic mean for relevant pairs $(o, p)^\star$

$\Rightarrow$ We establish a (semantic) connection between an invention p and a set of relevant occupations $o \in \mathcal{O}$


Unit Group 2431
Advertising and Marketing Professionals

Advertising and marketing professionals develop and coordinate advertising strategies and campaigns, determine the market for new goods and services, and identify and develop market opportunities for new and existing goods and services.

Tasks include –
(a) planning, developing and organizing advertising policies and campaigns to support sales objectives;
(b) advising managers and clients on strategies and campaigns to reach target markets, creating consumer awareness and effectively promoting the attributes of goods and services;
(c) writing advertising copy and media scripts, and arranging television and film production and media placement;
(d) collecting and analysing data regarding consumer patterns and preferences;
(e) interpreting and predicting current and future consumer trends;
(f) researching potential demand and market characteristics for new goods and services;
(g) supporting business growth and development through the preparation and execution of marketing objectives, policies and programmes;
(h) commissioning and undertaking market research to identify market opportunities for new and existing goods and services;
(i) advising on all elements of marketing such as product mix, pricing, advertising and sales promotion, selling and distribution channels.

Examples of the occupations classified here:
- Advertising specialist
- Marketing specialist
- Market research analyst

Weighting Scheme

- The weight assigned to a patent p is:

$$\omega_d^p = \frac{m_p}{\sum_{p \in \mathcal{P}_{dt}^k} m_p}$$

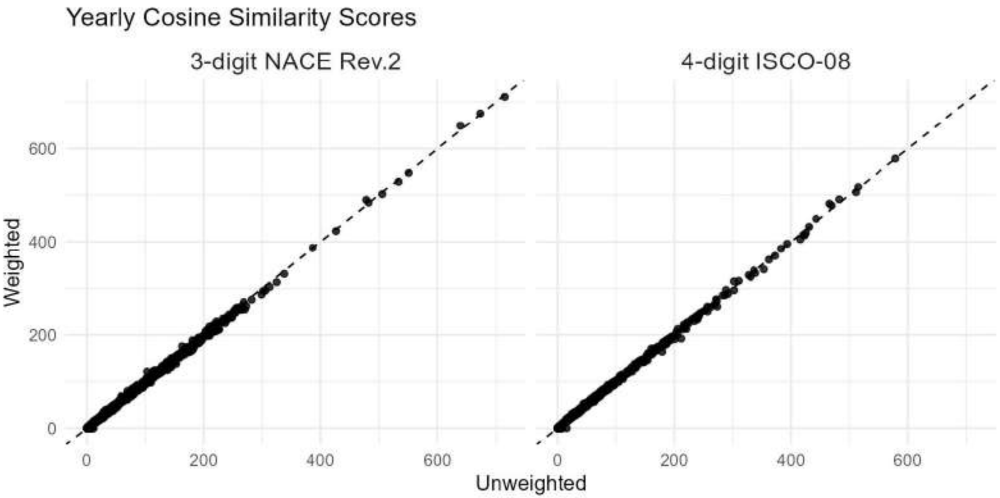
  - m_p is the number of citations received by patent p
  - $\mathcal{P}_{dt}^k$ is the set of patents belonging to emerging digital technology k, filed in year t, and relevant to industry/occupation $d = \{i, o\}$

- Aggregate to the technology level: $C_{dt}^k = |\mathcal{P}_{dt}^k| \times \sum_{p \in \mathcal{P}_{dt}^k} \omega_d^p C_d^p$

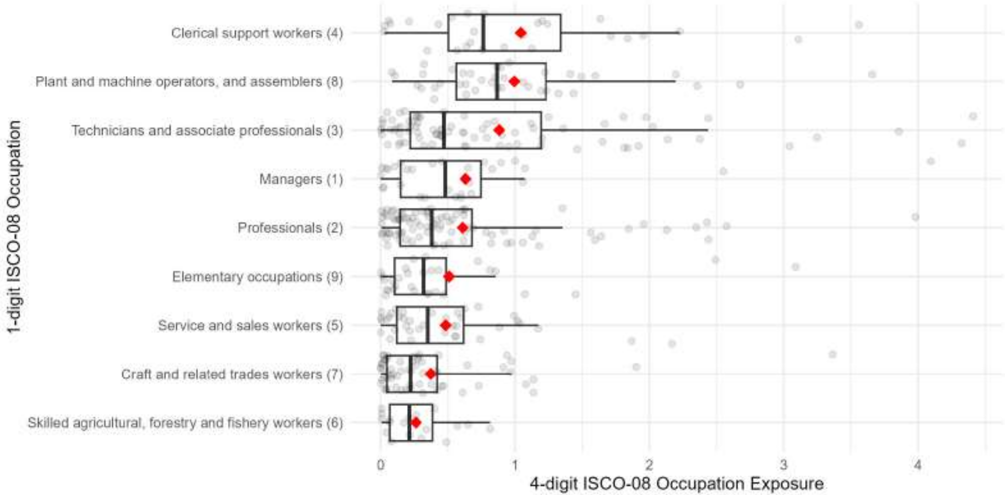
- Cumulative cosine similarity score for the period 2012–2021: $C_d^k = \sum_t C_{dt}^k$

Weighted versus Unweighted Yearly Cosine Similarity Scores

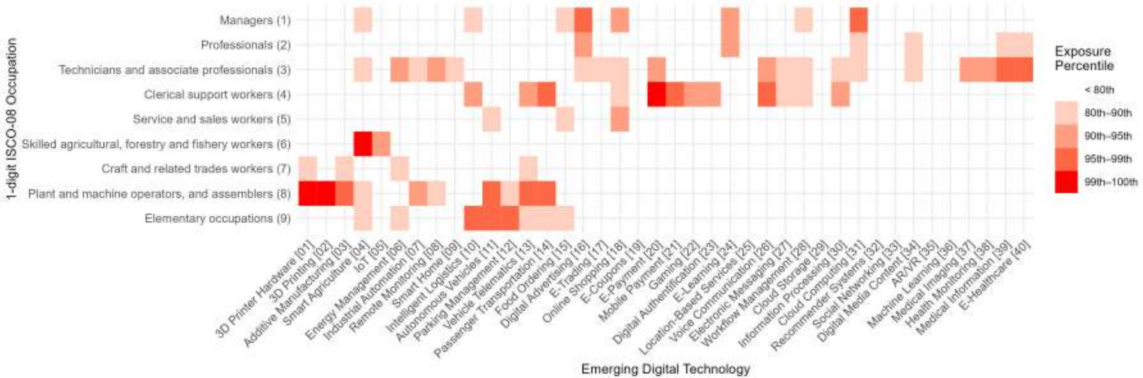
◂ Go back



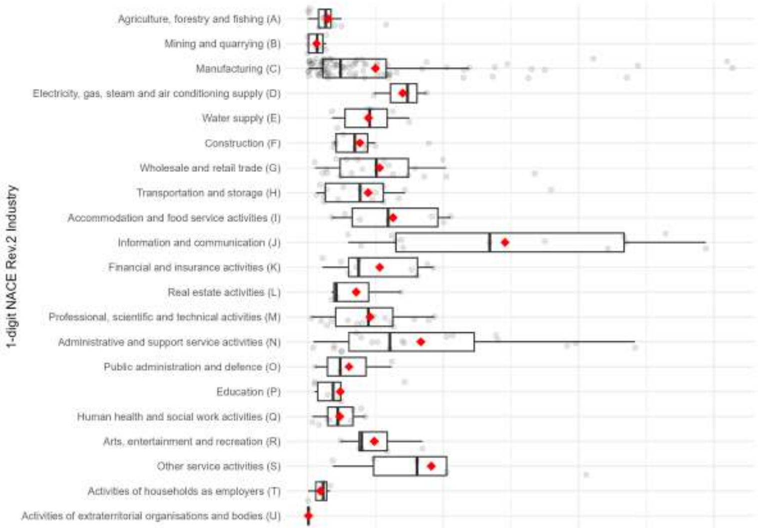
◂ Go back


Clerical support workers (4)
Plant and machine operators, and assemblers (8)
Technicians and associate professionals (3)
Managers (1)
Professionals (2)
Elementary occupations (9)
Service and sales workers (5)
Craft and related trades workers (7)
Skilled agricultural, forestry and fishery workers (6)
1-digit ISCO-08 Occupation
0
1
2
3
4
4-digit ISCO-08 Occupation Exposure

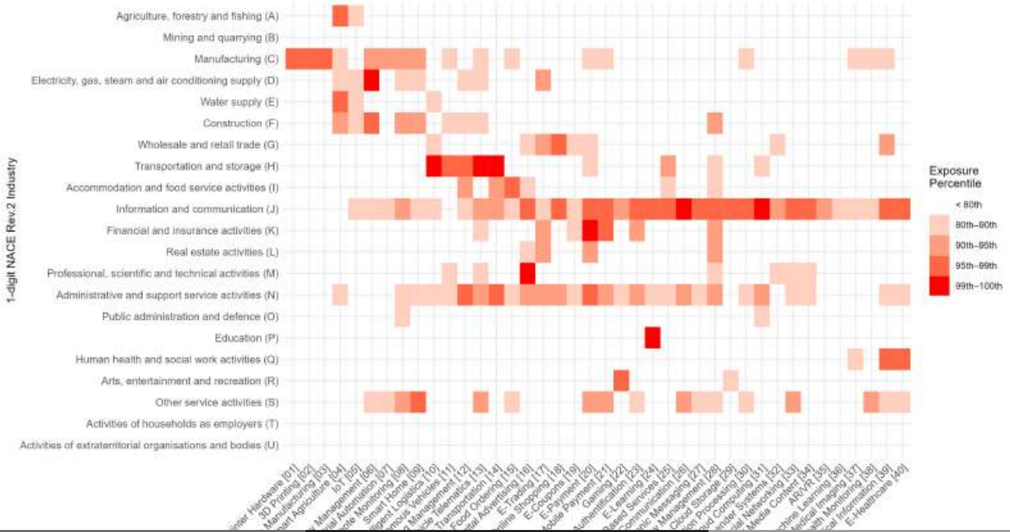
Go back


Managers (1)
Professionals (2)
Technicians and associate professionals (3)
Clerical support workers (4)
Service and sales workers (5)
Skilled agricultural, forestry and fishery workers (6)
Craft and related trades workers (7)
Plant and machine operators, and assemblers (8)
Elementary occupations (9)
1-digit ISCO-08 Occupation
3D Printer Hardware [01]
3D Printing [02]
Additive Manufacturing [03]
Smart Agriculture [04]
IoT [05]
Energy Management [06]
Industrial Automation [07]
Remote Monitoring [08]
Smart Home [09]
Intelligent Logistics [10]
Autonomous Vehicles [11]
Parking Management [12]
Vehicle Telematics [13]
Passenger Transportation [14]
Food Ordering [15]
Digital Advertising [16]
E-Trading [17]
Online Shopping [18]
E-Coupons [19]
E-Payment [20]
Mobile Payment [21]
Gaming [22]
Digital Authentification [23]
E-Learning [24]
Location-Based Services [25]
Voice Communication [26]
Electronic Messaging [27]
Workflow Management [28]
Cloud Storage [29]
Information Processing [30]
Cloud Computing [31]
Recommender Systems [32]
Social Networking [33]
Digital Media Content [34]
AR/VR [35]
Machine Learning [36]
Medical Imaging [37]
Health Monitoring [38]
Medical Information [39]
E-Healthcare [40]
Emerging Digital Technology
Exposure Percentile
< 80th
80th–90th
90th–95th
95th–99th
99th–100th

Go back


1-digit NACE Rev.2 Industry
Agriculture, forestry and fishing (A)
Mining and quarrying (B)
Manufacturing (C)
Electricity, gas, steam and air conditioning supply (D)
Water supply (E)
Construction (F)
Wholesale and retail trade (G)
Transportation and storage (H)
Accommodation and food service activities (I)
Information and communication (J)
Financial and insurance activities (K)
Real estate activities (L)
Professional, scientific and technical activities (M)
Administrative and support service activities (N)
Public administration and defence (O)
Education (P)
Human health and social work activities (Q)
Arts, entertainment and recreation (R)
Other service activities (S)
Activities of households as employers (T)
Activities of extraterritorial organisations and bodies (U)

◂ Go back


Agriculture, forestry and fishing (A)
Mining and quarrying (B)
Manufacturing (C)
Electricity, gas, steam and air conditioning supply (D)
Water supply (E)
Construction (F)
Wholesale and retail trade (G)
Transportation and storage (H)
Accommodation and food service activities (I)
Information and communication (J)
Financial and insurance activities (K)
Real estate activities (L)
Professional, scientific and technical activities (M)
Administrative and support service activities (N)
Public administration and defence (O)
Education (P)
Human health and social work activities (Q)
Arts, entertainment and recreation (R)
Other service activities (S)
Activities of households as employers (T)
Activities of extraterritorial organisations and bodies (U)
1-digit NACE Rev.2 Industry
Hardware [01]
3D Printing [02]
Manufacturing [03]
Agriculture [04]
IoT [05]
Management [06]
Automation [07]
Monitoring [08]
Smart Home [09]
Logistics [10]
Vehicles [11]
Management [12]
Telematics [13]
Transportation [14]
Food Ordering [15]
Advertising [16]
E-Trading [17]
Shopping [18]
E-Coupons [19]
E-Payment [20]
Payment [21]
Gaming [22]
Authentification [23]
E-Learning [24]
Services [25]
Communication [26]
Messaging [27]
Management [28]
Cloud Storage [29]
Processing [30]
Computing [31]
Systems [32]
Networking [33]
Media Content [34]
AR/VR [35]
Learning [36]
Imaging [37]
Monitoring [38]
Information [39]
E-Healthcare [40]
Exposure Percentile
< 80th
80th–90th
90th–95th
95th–99th
99th–100th

Comparison with Other Metrics in the Literature

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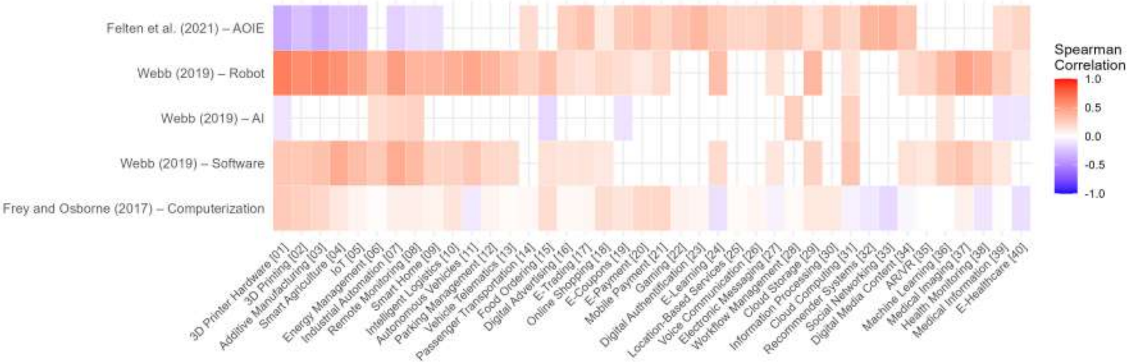

Average Employment Share by Sector of Activities in 2010

Go back

	NACE Sector	Emp. Share Mean	Emp. Share SD	Shock
A	Agriculture	0.068	0.010	0.42
B-E	Industry, excluding Construction	0.179	0.006	1.38
F	Construction	0.076	0.000	1.19
G-I	Market Services, excluding Information and Communication	0.238	0.001	1.94
J	Information and Communication	0.026	0.000	4.30
K	Financial and Insurance Activities	0.028	0.000	1.56
L	Real Estate Activities	0.007	0.000	0.95
M-N	Professional, Scientific, Technical, Administration and Support Services	0.083	0.001	2.59
O-Q	Public Administration, Defence, Education, Human Health and Social Work	0.237	0.004	0.70
R-U	Other Services	0.053	0.000	1.04

Notes: This table presents the employment share by sector of activities averaged across all the European regions in 2010. The first column indicates the 1-digit NACE codes, the second column is the name of the NACE sector, the third column is the average employment share in 2010, and the fourth column gives the standard errors.

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