The Employment Impact of Digital Technologies

Ekaterina Prytkova
University Côte d'Azur

Fabien Petit
UCL, CEPEO

Deyu Li
Utrecht University

Sugat Chaturvedi
Ahmedabad University

Tommaso Ciarli
UNU-MERIT

Digital Technologies and the Future of Work

- The past decade has seen rapid advancements in digital technologies
  - Networking (5G, IoT, Swarm), Robotic navigation and control (self-driving cars, Cobots), Enhanced UI (AR/VR, virtual assistants), Additive Manufacturing (AM), Artificial Intelligence (AI), Data Management and Security (blockchain).

- Impact of technologies on labor is complex
  - Displacement versus productivity/reinstatement effect (Acemoglu and Restrepo 2018)
  - Innovation and emerging markets (Vivarelli 1995)
  - Impact differs among technologies e.g. tangible (Robots, IoT) vs intangible (AI, VR) (Blanas 2023; Jestl 2024; Jaccoud et al. 2024)
  - Complementarities between emerging digital technologies (e.g. machine learning & cloud computing, industrial automation & remote monitoring) (Acemoglu et al. 2022; Jerbashian 2022; Bonney et al. 2024)

This Paper

- We measure the exposure of industries and occupations to 40 emerging digital technologies and estimate their impact on regional employment in Europe

Exposure

- For each 4-digit ISCO-08 occupation and 3-digit NACE industry, we obtain exposure score to 40 emerging digital technologies
- Based on semantic similarity between technology (i.e. cluster of patents) and descriptions of industries and occupations

Employment impact

- We estimate their impact on EU regional employment (2012–2019) using an IV shift–share
  - EU-LFS data with 320 NUTS-2 regions in 32 European countries

Preview of the results

1. High-skilled occupations (i.e. managers, professionals, and technicians) are among the most exposed, alongside mid-skilled occupations (i.e. machine operators and clerks)

2. Overall positive effect of digital exposure on employment
3. Job polarization; skewed in favor of high-skilled occupations (SBTC):
   - high heterogeneity among exposure effects on low-skilled labor across EU regions

4. Technology Complementarity matters when estimating labor effects of individual technologies
   - some techs deepen their employment effect ($\uparrow |\beta|$)
   - some techs change the direction of effect (sign of β)

Contributions

- Exposure to technology (Webb 2019; Kelly et al. 2021; Mann and Püttmann 2023; Autor et al. 2024)
  - Novel scalable methodology with Sentence Transformers
  - New 'TechXposure' Database
  - Technology as a cluster of patents → 40 emerging digital technologies
  - Overcoming limitations of previous exposure measures:
    - not stand-alone such as robots (Acemoglu and Restrepo 2020) or AI (Webb 2019; Felten et al. 2021)
    - not catch-all of automation technologies (Kogan et al. 2019; Mann and Püttmann 2023)
    - not keyword-based or bag-of-words (Kogan et al. 2021; Autor et al. 2024)
- Labor market impact of digital technologies (Arntz et al. 2017; Frey and Osborne 2017; Graetz and Michaels 2018; Acemoglu and Restrepo 2019)
  - Overall positive impact
  - Job polarization and SBTC
  - Control for tech complementarities to isolate true effects

Outline

Outline

1. Introduction
2. Text-as-Data
3. Descriptive Insights
4. Employment Impact
5. Conclusion

Derwent Innovation Index Patents

- A DII patent (family)
  - title, abstract with rubrics: novelty, use, claims, etc.
  - expertly curated structure; English translation

- Title structure: p_1:description of the invention, **has/includes/involves/comprises** p_2: *function/intended use of the invention*
- For instance, a patent on Targeted TV Advertising (2013B87254, 2013)

  "p_1: Method for targeting television advertisement based on profile linked to online device, **involves** p_2: *selecting television advertisement to be directed to set-top box based on profile information pertaining to user or online activity.*"

- Patent corpus: 190,714 digital automation patents identified in Chaturvedi et al. (2023) filed between 2012 and 2021

NACE Rev.2 Industries

- NACE Rev.2 Classification at 3-digit level: $|\mathcal{I}| = 272$ industries
- Textual representation: title and description $\forall\ i \in \mathcal{I}$

60.2 Television programming and broadcasting activities

Title

Description

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.

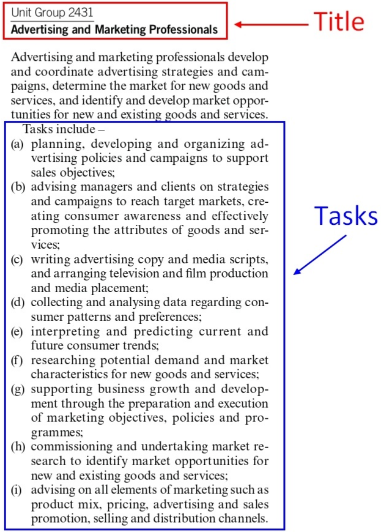
Exclude

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

ISCO-08 Occupations

- ISCO-08 Classification at 4-digit level: $|\mathcal{O}| = 436$ occupations
- Textual representation: title and a list of tasks $\forall\, o \in \mathcal{O}$



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.

Embeddings with Sentence Transformer

We use Sentence Transformer MPNet v2 (Song et al. 2020)

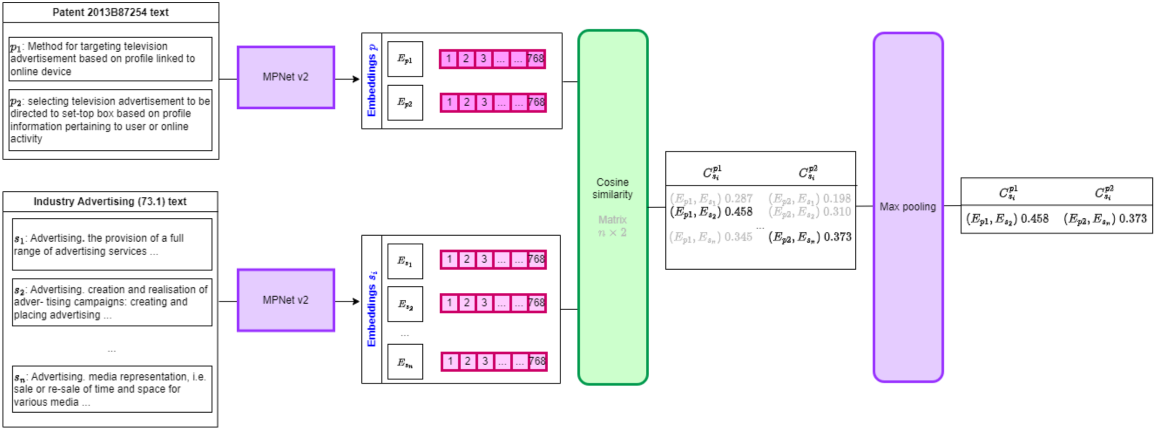
- transform texts—patents, industries, occupations—into embeddings, i.e. dense vector representations
- Advantages:
  - Contextual or dynamic embeddings instead of BoW or static embeddings used in Kogan et al. 2021; Autor et al. 2024
    $\rightarrow$ encoding of every word's meaning that accounts for its surrounding context
  - Trained for text similarity task using contrastive loss
    $\rightarrow$ ensures that distances between document-vectors represent their semantic (dis)similarity
- Cosine similarity $[-1; 1]$ between document-vectors as a measure of semantic (dis)similarity of documents' content

Digital Technologies with K-means Clustering

	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

Exposure Scores: Patent Level



Exposure Scores: Technology Level

- We aggregate patent cosine similarity scores C_i^p to the technology level to obtain C_i^k
  - Weighted sum based on the number of citations
- IHS Normalization: $X_i^k = \sinh^{-1}\left(C_i^k\right)$
- Finally, we obtain cumulative exposure X_i^k of each industry (occupation) to each of 40 technologies over the period 2012–2021

3-digit NACE code	Industry title (i)	Digital Technology (k)	X_i^k
28.2	M. of general-purpose machinery	3D Printer Hardware	8.79
28.9	M. 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

Exposure Scores: Interpretation

- Exposure scores indicate the (contextualized) relevance of each technology to a given industry or occupation, which is a proxy for adoption
- For industries: relevance is determined by the integration of a technology into the production process and/or if the technology enhances the output of an industry
- For occupations: relevance pertains to the importance of a technology in performing tasks and functions inherent to an occupation
- Exposure scores are neutral regarding the nature of the relationship between a technology and an industry/occupation

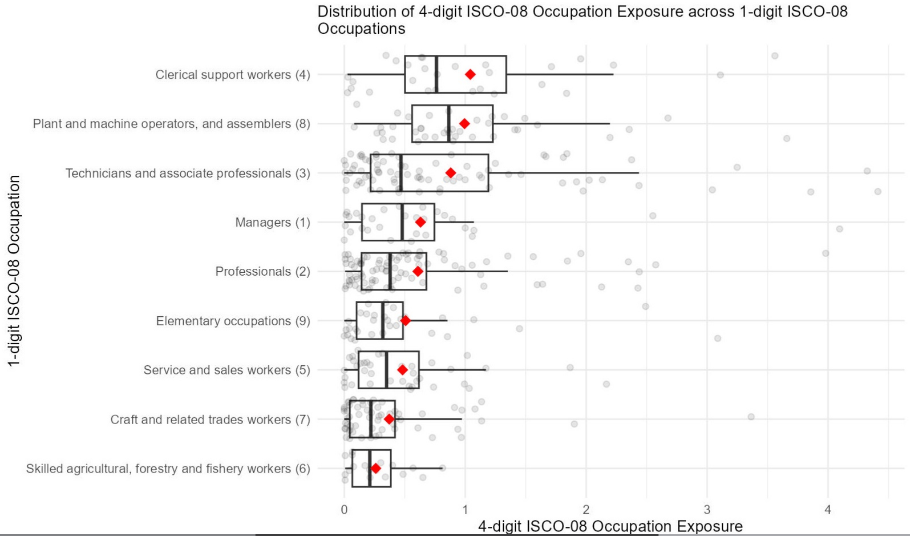
TechXposure Database (v0.9.0)

- TechXposure is an open–access database
- All aggregation levels: up to 4-digit ISCO-08 Occupations and 3-digit NACE Rev.2 Industries; yearly 2012-2021 and cumulative
- The database will be updated periodically (new technologies, new classifications)
  - Coming out soon O*NET/SOC and NAICS for the US context

Outline

1. Introduction
2. Text-as-Data
3. Descriptive Insights
4. Employment Impact
5. Conclusion

Distribution of Occupation Exposure by 1-digit ISCO-08 group

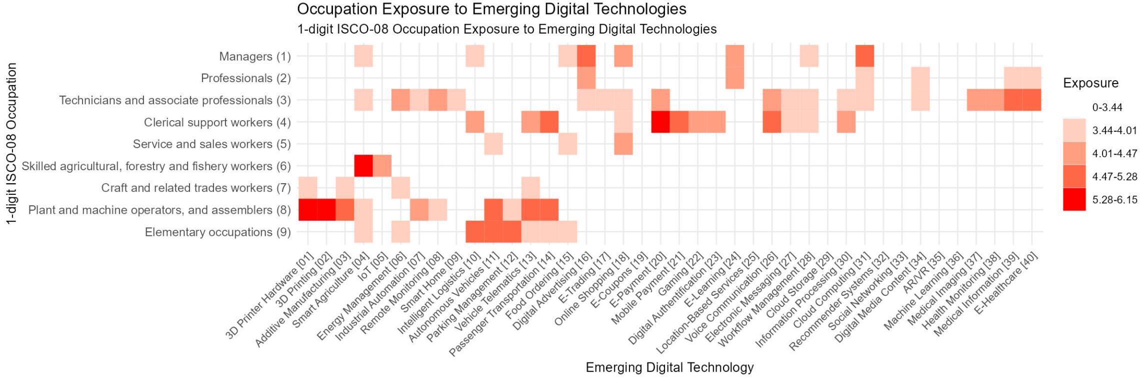


Top-10 Exposed Tasks

ISCO Occupation (1-digit Code)	Most exposed tasks
Managers (1)	specifying, consulting, computing, directing, monitoring, training, overseeing, determining, advertising, planning
Professionals (2)	monitoring, developing, planning, designing, recording, advising, providing, organizing, exchanging, advertising
Technicians and associate professionals (3)	monitoring, operating, controlling, recording, maintaining, assisting, transmitting, establishing, providing, keeping
Clerical support workers (4)	banking, operating, keeping, entering, processing, coordinating, preparing, registering, receiving, concerning
Service and sales workers (5)	arranging, processing, demonstrating, receiving, serving, maintaining, driving, checking, operating, explaining
Skilled agricultural, forestry, fishery workers (6)	monitoring, coordinating, planning, determining, maintaining, operating, cultivating, setting, pruning, thinning, transplanting
Craft and related trades workers (7)	setting, installing, monitoring, repairing, providing, creating, adjusting, maintaining, using, wiring
Plant and machine operators, and assemblers (8)	operating, monitoring, moulding, driving, controlling, tending, observing, finishing, papermaking, cutting
Elementary occupations (9)	delivering, moving, collecting, driving, reading, recording, parking, carrying, keeping, sorting

Occupation Exposure Breakdown by Technology

▸ Other Scores



Outline

Effect of Technological Change on Employment

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

where

- ΔY_r is the change in the regional $\frac{\textit{Employment}}{\textit{population}}$ 2012-2019 (in pp.)
- $X_r = \sum_j l_{rj} X_j$ is the shift-share regional exposure
- Z is a set of covariates, $\phi_{c(r)}$ are country FE, and u_r the error term

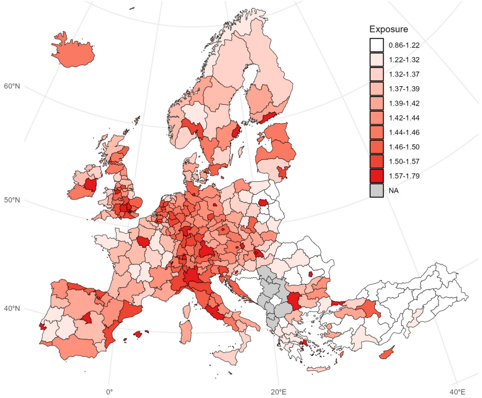
- Labour data: Regional European Labour Force Survey (EU-LFS)
  - Sample: 320 NUTS-2 European regions from 32 European countries
  - Employment in 10 *broad* sectors of activities: groups of 1–digit NACE industries
  - Demographic controls
- Technological change: TechXposure – cumulative exposure scores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

Shift-Share IV: Regional Exposure

- shift–share strategy to instrument the regional exposure to digital technologies (Adão et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2021)

$$X_r = \sum_j \underbrace{l_{rj}}_{\text{Share}} \cdot \underbrace{X_j}_{\text{Shock}},$$

  - Share: l_{rj} is the employment share of sector j in region r in 2010
  - Shock: X_j is the average exposure of sector j to *all* digital technologies (2012–2019)



- Identifying assumptions:
  1. Shock exogeneity: Quasi-random assignment of shocks – 7% of EU patents

  2a. The number of observed shocks is sufficiently large (HHI is $\sum_j l_j^2 = 0.168$)

  2b. More exposed regions are not disproportionately affected by other labor market shocks/trends

Exposure Effect on Regional Employment by Demographic and Skill Groups

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) $\times$ 100							
	All	Gender		Age		Skill		
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
Exposure	0.918^{***}	0.629^{***}	0.288^{***}	0.140^{***}	0.779^{***}	0.530^{*}	-0.299^{***}	0.707^{***}
	(0.141)	(0.119)	(0.031)	(0.027)	(0.120)	(0.241)	(0.065)	(0.128)
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 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.

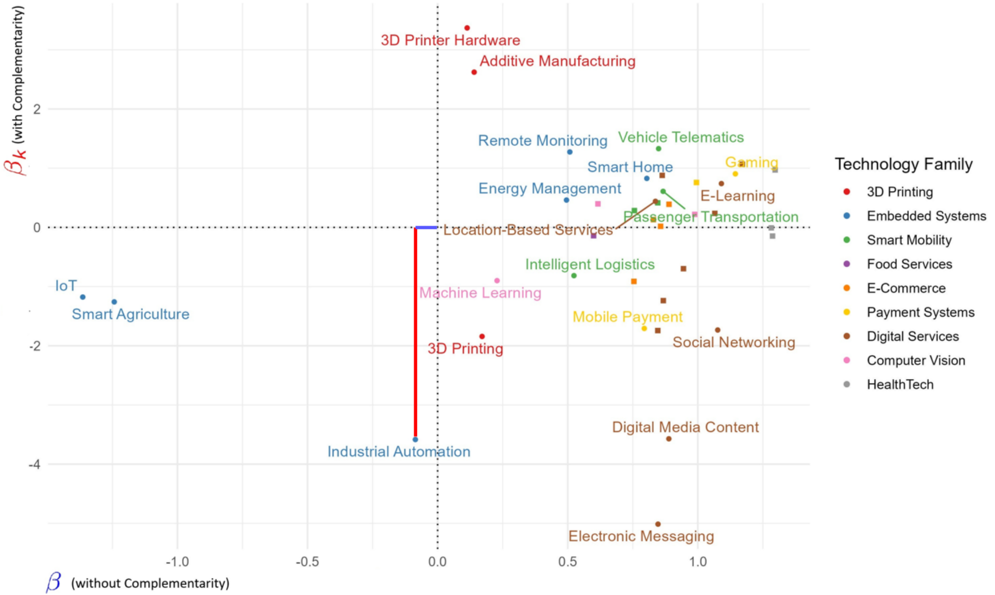
Technological Complementarity (TC)

$$\Delta Y_r = \alpha + \beta_k X_r^k + \qquad + Z\delta + \phi_{c(r)} + u_r,$$

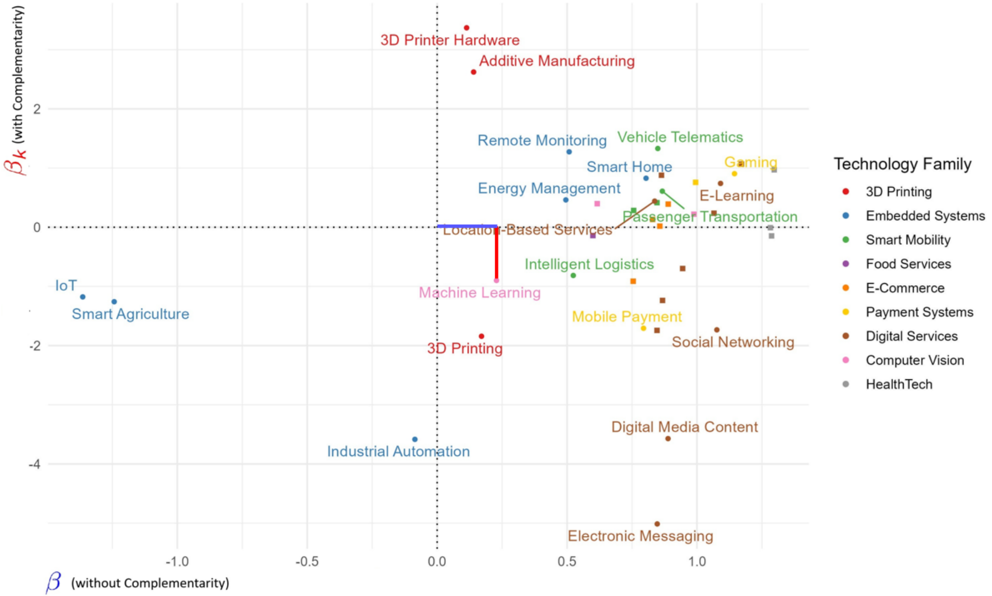
$$\Delta Y_r = \alpha + \underbrace{\beta_k X_r^k}_{\text{Focal Tech } k} + \underbrace{\gamma_{1k} X_r^{K\setminus\{k\}}}_{\text{Within-Family Complementarity}} + \underbrace{\gamma_{2k} X_r^{-K}}_{\text{Between-Family Complementarity}} + Z\delta + \phi_{c(r)} + u_r$$

- X_r^k exposure to the focal technology k
- $X_r^{K\setminus\{k\}}$ exposure to the focal technology's family
- X_r^{-K} exposure to the rest of the technologies

- Main idea
  - isolate effect of individual technology k by accounting for its complementary technologies
  - TC exists if $\beta_k \neq \beta_k$



β_k (with Complementarity)
β (without Complementarity)
2
0
-2
-4
-1.0
-0.5
0.0
0.5
1.0
3D Printer Hardware
Additive Manufacturing
Remote Monitoring
Vehicle Telematics
Smart Home
Gaming
Energy Management
E-Learning
Passenger Transportation
Location-Based Services
Intelligent Logistics
IoT
Machine Learning
Smart Agriculture
Mobile Payment
3D Printing
Social Networking
Digital Media Content
Industrial Automation
Electronic Messaging
Technology Family
3D Printing
Embedded Systems
Smart Mobility
Food Services
E-Commerce
Payment Systems
Digital Services
Computer Vision
HealthTech



3D Printer Hardware
Additive Manufacturing
Remote Monitoring
Vehicle Telematics
Smart Home
Gaming
Energy Management
E-Learning
Passenger Transportation
Location-Based Services
Intelligent Logistics
IoT
Machine Learning
Smart Agriculture
Mobile Payment
Social Networking
3D Printing
Digital Media Content
Industrial Automation
Electronic Messaging
β_k (with Complementarity)
β (without Complementarity)
2
0
-2
-4
-1.0
-0.5
0.0
0.5
1.0
Technology Family
3D Printing
Embedded Systems
Smart Mobility
Food Services
E-Commerce
Payment Systems
Digital Services
Computer Vision
HealthTech

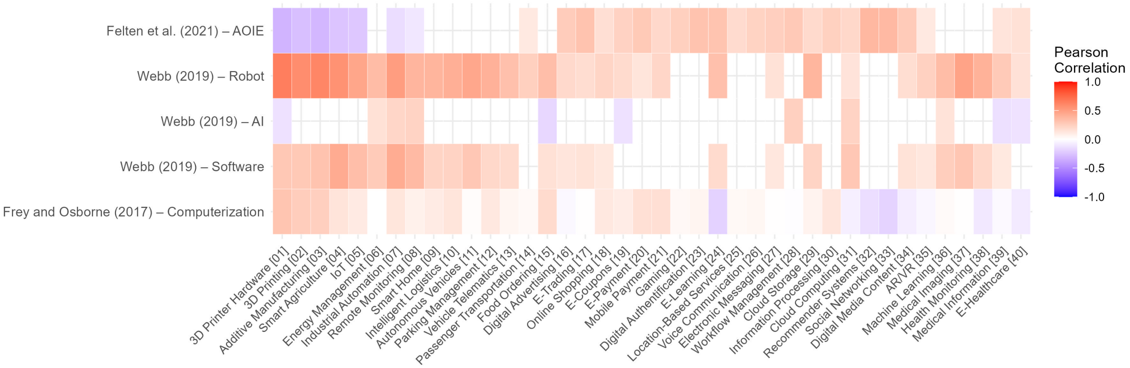
Outline

Conclusion

- We measure the exposure of industries and occupations to emerging digital technologies and estimate their impact on employment in Europe
  - TechXposure Database available on GitHub
- Main takeaways:
  1. High-skilled are among most exposed
  2. Overall positive impact on employment
  3. Job polarization and SBTC
  4. Effects on low-skilled labor differ across regions
  5. Tech complementarities matter for isolation of individual technology effects
- Contact: Ekaterina.Prytkova@univ-cotedazur.fr
- Related research: check my Google Scholar page

Comparison with Other Exposure Scores

Back



References I

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childress, E., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger, J., Kroff, Z., Restrepo, P., and Zolas, N. (2022). Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey. Working Paper 2049427, National Bureau of Economic Research.

Acemoglu, D. and Restrepo, P. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108:1488–1542.

Acemoglu, D. and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33:3–30.

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128:2188–2244.

Adão, R., Kolesár, M., and Morales, E. (2019). Shift-Share Designs: Theory and Inference. *The Quarterly Journal of Economics*, 134(4):1949–2010.

Arntz, M., Gregory, T., and Zierahn, U. (2017). Revisiting the Risk of Automation. *Economics Letters*, 159:157–160.

References II

Autor, D., Chin, C., Salomons, A., and Seegmiller, B. (2024). New Frontiers: The Origins and Content of New Work, 1940–2018. *The Quarterly Journal of Economics*, 139(3):1399–1465.

Blanas, S. (2023). The distinct effects of information technologies and communication technologies on skill demand. *Industrial Relations: A Journal of Economy and Society*.

Bonney, K., Breaux, C., Buffington, C., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., and Savage, K. (2024). Tracking Firm Use of AI in Real Time: A Snapshot from the Business Trends and Outlook Survey.

Borusyak, K., Hull, P., and Jaravel, X. (2021). Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies*, 89(1):181–213.

Chaturvedi, S., Prytkova, E., Ciarli, T., and Nomaler, O. (2023). What's the Future of Automation? Using Semantic Analysis to Identify Emerging Technologies. Working paper.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and its Potential Uses. *Strategic Management Journal*, 42(12):2195–2217.

Frey, C. B. and Osborne, M. A. (2017). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114:254–280.

References III

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review*, 110(8):2586–2624.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100:753–768.

Jaccoud, F., Petit, F., Ciarli, T., and Savona, M. (2024). Automation and Employment Over the Technology Life Cycle: Evidence from European Regions.

Jerbashian, V. (2022). On the Elasticity of Substitution between Labor and ICT and IP Capital and Traditional Capital. *SSRN Electronic Journal*.

Jestl, S. (2024). Industrial robots, and information and communication technology: the employment effects in EU labour markets. *Regional Studies*.

Kelly, B., Papanikolaou, D., Seru, A., and Taddy, M. (2021). Measuring Technological Innovation over the Long Run. *American Economic Review: Insights*, 3(3):303–320.

Kogan, L., Papanikolaou, D., Schmidt, L., and Seegmiller, B. (2019). Technological Change and Occupations over the Long Run. Working paper.

Kogan, L., Papanikolaou, D., Schmidt, L., and Seegmiller, B. (2021). Technology-Skill Complementarity and Labor Displacement: Evidence from Linking Two Centuries of Patents with Occupations. Working paper.

References IV

Mann, K. and Püttmann, L. (2023). Benign Effects of Automation: New Evidence from Patent Texts. *Review of Economics and Statistics*, 105(3):562–579.

Song, K., Tan, X., Qin, T., Lu, J., and Liu, T.-Y. (2020). Mpnet: Masked and permuted pre-training for language understanding. *Advances in Neural Information Processing Systems*, 33:16857–16867.

Vivarelli, M. (1995). *The Economics of Technology and Employment: Theory and Empirical Evidence*. Edward Elgar Publishing.

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. Working paper.