The Employment Impact of Emerging Digital Technologies: Evidence from US Labor Markets

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Emerging Digital Technologies Shape the Future of Work

- Emerging digital technologies have transformed the global economy through widespread digitalization
  - e.g., artificial intelligence (AI), electric vehicles, drones, the Internet of Things (IoT), and robotics
- They reshape the nature of work, impacting workers in uneven ways
  - Enhanced productivity, new job opportunities, and task displacement (Acemoglu and Restrepo 2018)

⇒ Which occupations and industries are most affected by these changes? Which demographic and skill groups are most vulnerable?

This Paper

- We measure the exposure of industries and occupations to emerging digital technologies and estimate their impact on US employment

Exposure. *Using the methodology from* Prytkova et al. (2024) *adapted to the US context*

- We obtain exposure scores of 1,110 8-digit O*NET-SOC 2010 occupations and 324 4-digit NAICS 2007 industries to 40 digital technologies that emerged between 2012 and 2021
- Open–access TechXposure database

Employment Impact.

- We estimate their impact on US employment and among different demographic and skill groups (2012–2019) using an IV shift–share
  - American Community Survey (ACS) Data with 741 Commuting Zones (CZ)

Preview of the Results

1. Overall positive impact of digital technologies
   - 1-SD increase in CZ exposure ⇒ 0.67 pp. (1.1%) increase in the CZ employment-to-population ratio
2. Substantial heterogeneity among demographic groups
   - Positive employment effects for young workers (ages 16–24) and senior workers (ages 45–64)
   - Negative impact for core working-age individuals (ages 25–44)
   - No significant differences in impact across gender
3. Skill-biased technological change
   - Negative impact on workers with a high school education or less, whereas a positive impact is noted for college graduates

Contributions

- The changing nature of work due to technological change
  - Computerization (Frey and Osborne 2017), industrial robots (Acemoglu and Restrepo 2020), specific applications of AI (Webb 2019, Felten et al. 2021, Felten et al. 2018, Hampole et al. 2025), or a broad spectrum of technologies (Autor et al. 2024, Kogan et al. 2017, Kogan et al. 2017).

  ⇒ Wider array of new and detailed digital technologies with measures of exposure at a very granular level for the US context using a state-of-the-art NLP approach

- Impact of digital technologies on US employment
  - Industrial robots: negative (Acemoglu and Restrepo 2020); AI: mixed (Webb 2019, Bonfiglioli et al. 2024, Hampole et al. 2025); broader definition of automation technologies: positive (Mann and Püttmann 2023, Autor et al. 2024) with skill-biased technological change (Kogan et al. 2021)

  ⇒ We find a positive overall impact on US employment with significant heterogeneity across different age groups and educational levels

From Patents to Emerging Digital Technologies

- We use the sample of patents identified as core digital inventions in Chaturvedi et al. (2023)
  - Filed between 2012 and 2021 (extracted from Derwent Database)
- These patents are grouped into 40 distinct technologies based on semantic similarities in their titles in Prytkova et al. (2024)

9 Technology Families: 40 Emerging Technologies

▸ Distribution

	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

Methodology to Derive Exposure Scores

1. We preprocess the textual data from patents, industries, and occupations
   - 4-digit NAICS 2007 industries and 8-digit O*NET-SOC 2010 occupations
2. We transform these preprocessed texts into contextual embeddings (i.e., dense vector representations) using the pre-trained MPNet v2 sentence transformer (Song et al. 2020)
   - Contextual embeddings consider the surrounding context of a word as compared to bag-of-word methods (e.g., Webb 2019, Autor et al. 2024)
3. We compute the cosine similarity between each patent–industry and patent–occupation pair of embeddings
   - Filter out irrelevant or mistaken connections (false positives)
4. We aggregate these exposure scores from the patent level up to the technology level
   - Patents are weighted by the number of citations relative to the total number of citations all patents filed in the same year received
   - We adjust for the right skewness of the exposure scores

Exposure Scores (for industries)

▸ Weighting Scheme

- We obtain cumulative exposure X_i^k of each industry to each of 40 technologies over the period 2012–2021
  - Same for occupations

Table: Top 5 Exposure Score Pairs

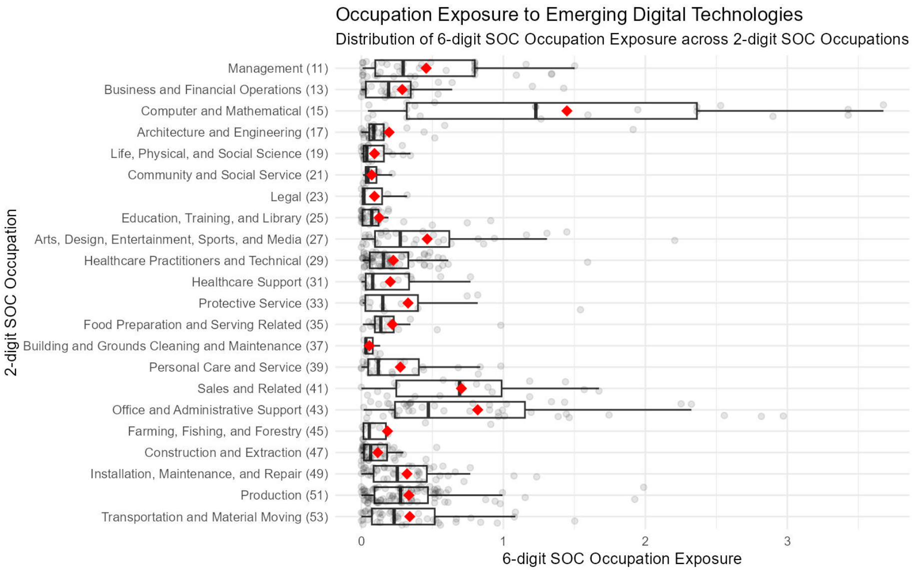
4-digit NAICS	NAICS Industry Title (i)	Digital Technology (k)	X_i^k
5223	Activities Related to Credit Intermediation	E-Payment	9.01
5418	Advertising, Public Relations, and Related Services	Digital Advertising	8.41
4541	Electronic Shopping and Mail-Order Houses	E-Payment	8.32
5221	Depository Credit Intermediation	E-Payment	8.28
4541	Electronic Shopping and Mail-Order Houses	Online Shopping	8.27

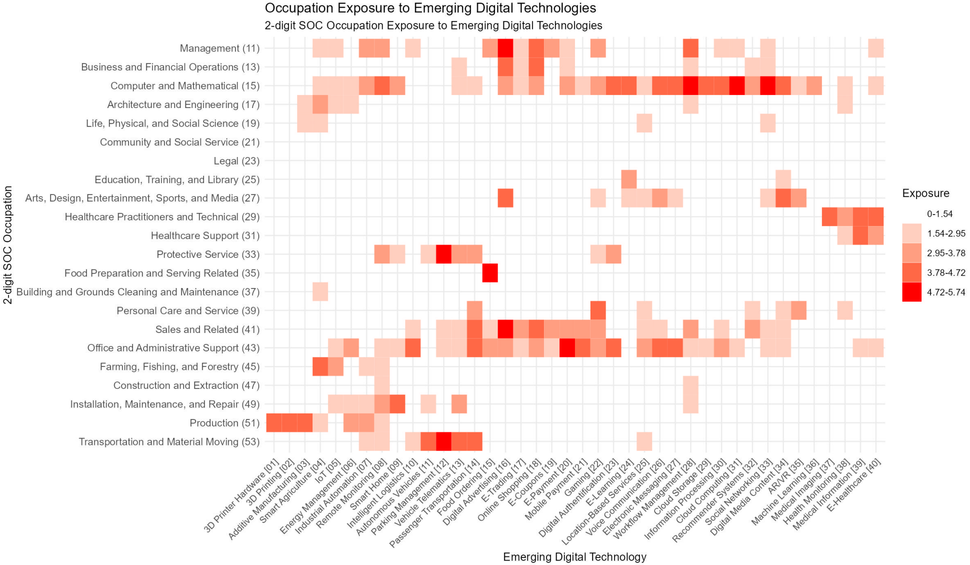
Interpreting Exposure Scores

- Exposure scores are the measure of relevance of a technology to an industry or occupation
  - For industries: integration of a technology into the production process and/or if the technology enhances the output of an industry
  - For occupations: importance of a technology in performing tasks and functions inherent to an occupation
- They indicate the potential for adoption, but *de facto* adoption might not have happened yet
  - Proxy for actual adoption
- Exposure scores are neutral regarding the relationship between technology and labor

Updating the TechXposure Database (v0.9.1)

- We deliver these new data as an update of the open–access TechXposure database
- Available here (soon): github.com/FabienPetitEconomics/TechXposure
- All aggregation levels: up to 8-digit SOC 2010 Occupations and 4-digit NAICS 2007 Industries
- The database will be updated periodically (new technologies, new classifications)
  - ISCO-08 and NACE Rev.2 already available


Occupation Exposure to Emerging Digital Technologies
Distribution of 6-digit SOC Occupation Exposure across 2-digit SOC Occupations
2-digit SOC Occupation
Management (11)
Business and Financial Operations (13)
Computer and Mathematical (15)
Architecture and Engineering (17)
Life, Physical, and Social Science (19)
Community and Social Service (21)
Legal (23)
Education, Training, and Library (25)
Arts, Design, Entertainment, Sports, and Media (27)
Healthcare Practitioners and Technical (29)
Healthcare Support (31)
Protective Service (33)
Food Preparation and Serving Related (35)
Building and Grounds Cleaning and Maintenance (37)
Personal Care and Service (39)
Sales and Related (41)
Office and Administrative Support (43)
Farming, Fishing, and Forestry (45)
Construction and Extraction (47)
Installation, Maintenance, and Repair (49)
Production (51)
Transportation and Material Moving (53)
0
1
2
3
6-digit SOC Occupation Exposure


Occupation Exposure to Emerging Digital Technologies
2-digit SOC Occupation Exposure to Emerging Digital Technologies
2-digit SOC Occupation
Management (11)
Business and Financial Operations (13)
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Life, Physical, and Social Science (19)
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Production (51)
Transportation and Material Moving (53)
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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]
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E-Learning [24]
Location-Based Services [25]
Voice Communication [26]
Electronic Messaging [27]
Workflow Management [28]
Cloud Storage [29]
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Cloud Computing [31]
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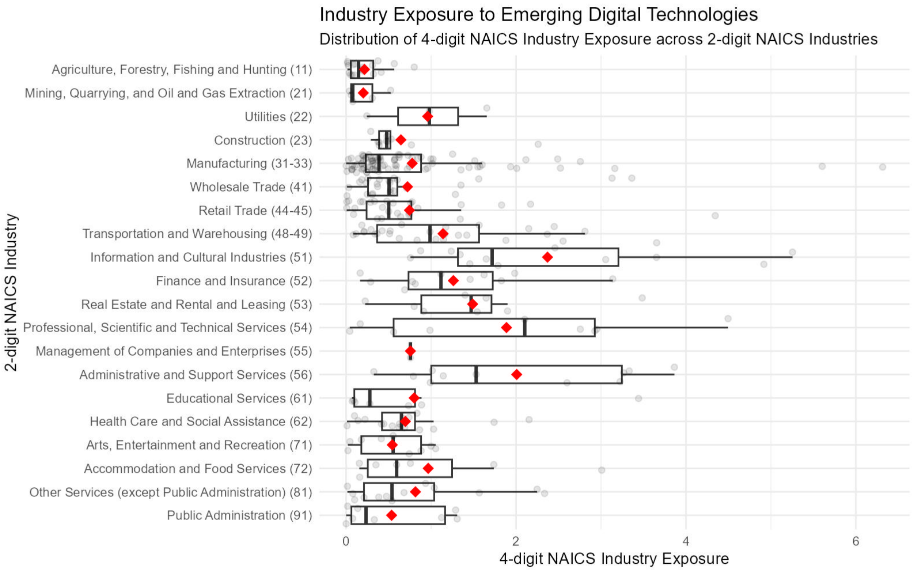
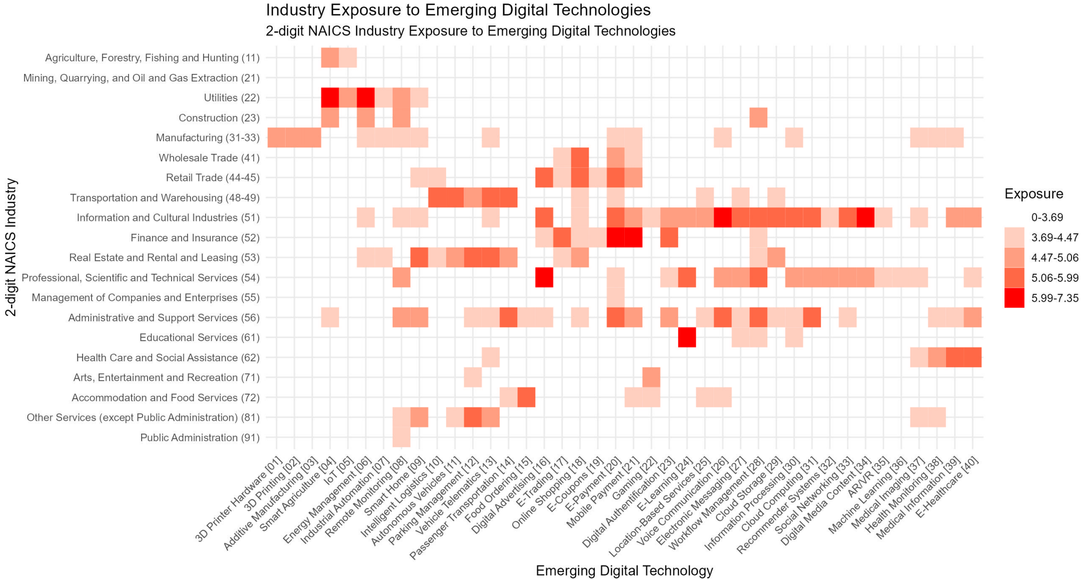
Social Networking [33]
Digital Media Content [34]
AR/VR [35]
Machine Learning [36]
Medical Imaging [37]
Health Monitoring [38]
Medical Information [39]
E-Healthcare [40]
Emerging Digital Technology
Exposure
0-1.54
1.54-2.95
2.95-3.78
3.78-4.72
4.72-5.74


Industry Exposure to Emerging Digital Technologies
Distribution of 4-digit NAICS Industry Exposure across 2-digit NAICS Industries
2-digit NAICS Industry
Agriculture, Forestry, Fishing and Hunting (11)
Mining, Quarrying, and Oil and Gas Extraction (21)
Utilities (22)
Construction (23)
Manufacturing (31-33)
Wholesale Trade (41)
Retail Trade (44-45)
Transportation and Warehousing (48-49)
Information and Cultural Industries (51)
Finance and Insurance (52)
Real Estate and Rental and Leasing (53)
Professional, Scientific and Technical Services (54)
Management of Companies and Enterprises (55)
Administrative and Support Services (56)
Educational Services (61)
Health Care and Social Assistance (62)
Arts, Entertainment and Recreation (71)
Accommodation and Food Services (72)
Other Services (except Public Administration) (81)
Public Administration (91)
0
2
4
6
4-digit NAICS Industry Exposure


Industry Exposure to Emerging Digital Technologies
2-digit NAICS Industry Exposure to Emerging Digital Technologies
2-digit NAICS Industry
Agriculture, Forestry, Fishing and Hunting (11)
Mining, Quarrying, and Oil and Gas Extraction (21)
Utilities (22)
Construction (23)
Manufacturing (31-33)
Wholesale Trade (41)
Retail Trade (44-45)
Transportation and Warehousing (48-49)
Information and Cultural Industries (51)
Finance and Insurance (52)
Real Estate and Rental and Leasing (53)
Professional, Scientific and Technical Services (54)
Management of Companies and Enterprises (55)
Administrative and Support Services (56)
Educational Services (61)
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Arts, Entertainment and Recreation (71)
Accommodation and Food Services (72)
Other Services (except Public Administration) (81)
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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
0-3.69
3.69-4.47
4.47-5.06
5.06-5.99
5.99-7.35

Effect of Technological Change on Employment

- We estimate the following empirical specification:

$$\Delta Y_c = \alpha + \beta X_c + Z\delta + \phi_{s(c)} + u_c$$

  - ΔY_c is the change in the CZ employment-to-population ratio 2012-2019 (in pp.)
  - X_c is the CZ exposure to emerging digital technologies
  - Z is a set of covariates, $\phi_{s(c)}$ are state FE, and u_c the error term

- American Community Survey (ACS) Data
  - Sample: 740 Commuting Zones (CZ) using Dorn (2009) crosswalk
  - Employment in 2–digit NAICS industries
  - Demographic controls
- TechXposure Database: Cumulative exposure scores 2012-2019 by industry

Shift-Share IV: Regional Exposure to Emerging Digital Technologies

- Shift–share IV (Borusyak et al. 2021):

$$X_c = \sum_j \underbrace{l_{cj}}_{\text{Share}} \cdot \underbrace{X_j}_{\text{Shock}},$$

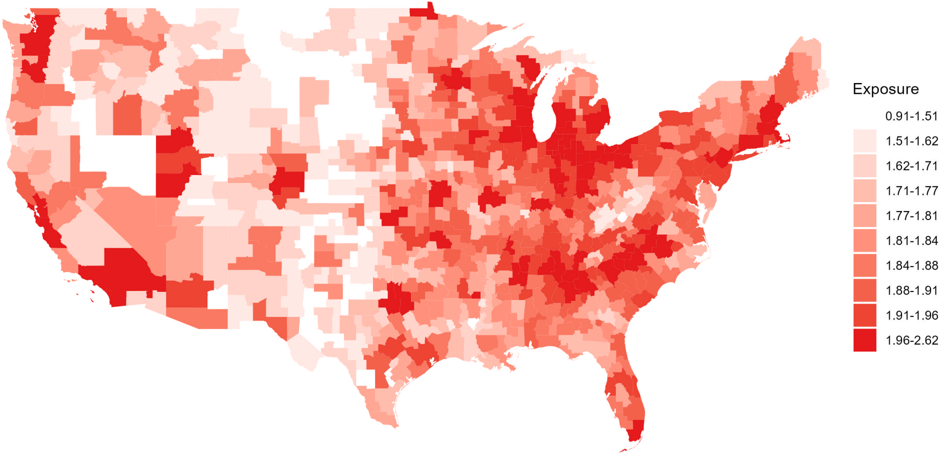
  - l_{cj} is the employment share of sector j in area c in 2010 ▸ Details
  - X_j is the average exposure of sector j to *all* emerging digital technologies (2012–2019)

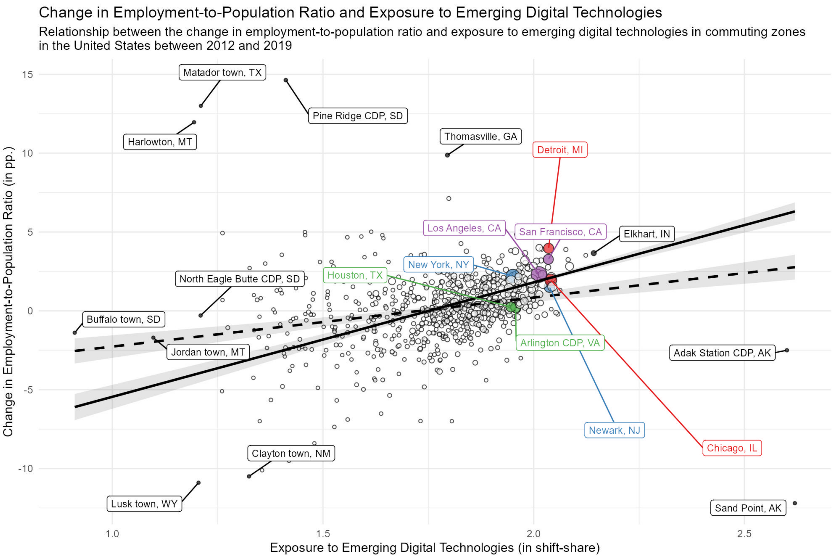
- Identifying assumptions:
  1. Shock exogeneity: Quasi-random assignment of shocks – 36% of US patents (excluded)

  2a. The number of observed shocks is sufficiently large (HHI is $\sum_j l_j^2 = 0.077$)

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

CZ Exposure to Digital Technologies (2012–2019)




Change in Employment-to-Population Ratio and Exposure to Emerging Digital Technologies
Relationship between the change in employment-to-population ratio and exposure to emerging digital technologies in commuting zones in the United States between 2012 and 2019
Change in Employment-to-Population Ratio (in pp.)
Exposure to Emerging Digital Technologies (in shift-share)
15
10
5
0
-5
-10
1.0
1.5
2.0
2.5
Matador town, TX
Pine Ridge CDP, SD
Harlowton, MT
Thomasville, GA
Detroit, MI
Los Angeles, CA
San Francisco, CA
Elkhart, IN
New York, NY
Houston, TX
North Eagle Butte CDP, SD
Buffalo town, SD
Jordan town, MT
Arlington CDP, VA
Adak Station CDP, AK
Newark, NJ
Chicago, IL
Clayton town, NM
Lusk town, WY
Sand Point, AK

Overall Impact of Emerging Digital Technologies on CZ Employment

	IV – Dep. var: Δ Emp-to-pop. Ratio (2012-2019) × 100						
	Weighted				Unweighted		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure to Digital Technologies	0.94***	0.67***	0.92***	0.81**	0.08	0.55**	0.76***
	(0.12)	(0.11)	(0.16)	(0.21)	(0.16)	(0.19)	(0.09)
State FE	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓
Industry share			✓	✓	✓	✓	✓
Exclude Top 10% Exp. CZ				✓			
Exclude Bottom 10% Pop. CZ						✓	
Exclude Bottom 20% Pop. CZ							✓
R^2	0.57	0.60	0.61	0.49	0.25	0.33	0.41
Adj. R^2	0.54	0.57	0.58	0.44	0.18	0.27	0.35
Num. obs.	741	741	741	666	741	666	592

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 census division 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.

Decomposing the Impact by Demographic Groups

	IV – Dep. var: Δ Emp-to-pop. Ratio (2012–2019) × 100								
	Gender (Y16-64)		Age						
	Female	Male	Y16-19	Y20-24	Y25-44	Y45-54	Y55-64	Y65-74	Y75+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exposure to Digital Technologies	0.20**	0.27***	0.15***	0.12**	−0.45***	0.43***	0.38***	0.03	0.01**
	(0.08)	(0.07)	(0.02)	(0.06)	(0.11)	(0.11)	(0.07)	(0.03)	(0.01)
Emp-to-pop. Ratio in 2012	0.26	0.28	0.02	0.05	0.25	0.14	0.09	0.02	0.00
Change (in %)	0.75	0.94	7.02	2.02	−1.70	3.01	4.00	1.42	2.64
R^2	0.55	0.53	0.41	0.38	0.45	0.75	0.62	0.38	0.20
Adj. R^2	0.51	0.49	0.36	0.33	0.41	0.73	0.59	0.33	0.13
Num. obs.	741	741	741	741	741	741	741	741	741

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. Demographic controls (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. Low-, middle-, and high-skilled workers are defined by educational level (i.e., high school or less, some college, and bachelor's degree or higher).

Decomposing the Impact by Education Groups

	IV – Dep. var: Δ Emp-to-pop. Ratio (2012–2019) $\times$ 100			
	Less HS	HS	Some Coll.	Bach.+
	(1)	(2)	(3)	(4)
Exposure to Digital Technologies	-0.05^{**}	-0.16^{**}	0.22^{**}	0.35^{**}
	(0.02)	(0.06)	(0.07)	(0.13)
Emp-to-pop. Ratio in 2012	0.04	0.12	0.15	0.17
Change (in %)	-1.08	-1.32	1.41	2.05
R^2	0.56	0.62	0.47	0.60
Adj. R^2	0.52	0.59	0.43	0.57
Num. obs.	741	741	741	741

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. Demographic controls (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. Low-, middle-, and high-skilled workers are defined by educational level (i.e., high school or less, some college, and bachelor's degree or higher).

Timing of the Impact on Employment

- We estimate the impact of digital technologies on the employment-to-population ratio over two sub-periods (2012–2016 and 2016–2019)

- We recalibrate the shift-share exposure of CZs for each period $t = \{1, 2\}$ as follows:

$$X_c^t = \sum_j l_{cj} X_j^t,$$

  where X_j^t is the average exposure score of each 2-digit NAICS industry to all digital technologies during the period t

- Cumulative development of digital technologies: X_c^1 and X_c^2 are highly correlated

- To address this, we calculate the change in exposure across the periods as $\Delta X_c \equiv X_c^2 / X_c^1$
  - Intensification of digital technology exposure in the second period relative to the first

Effect of Digital Technologies on US Employment by Periods

	IV – Dep. var: Δ Emp-to-pop. Ratio × 100				
	2012–2016		2016–2019		2012–2019
	(1)	(2)	(3)	(4)	(5)
Exposure P1 (2012–2016)	0.36**	0.37**		0.45***	0.82***
	(0.09)	(0.13)		(0.19)	(0.21)
Exposure P2 (2016–2019)			0.30***		
			(0.08)		
Exposure P2/P1		0.01		0.23*	0.24
		(0.21)		(0.16)	(0.24)
R^2	0.44	0.44	0.56	0.56	0.61
Adj. R^2	0.40	0.40	0.52	0.52	0.57
Num. obs.	741	741	741	741	741

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. Demographic controls (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. Low-, middle-, and high-skilled workers are defined by educational level (i.e., high school or less, some college, and bachelor's degree or higher).

Conclusion

- We measure the exposure of industries and occupations to emerging digital technologies and estimate their impact on US employment
  - TechXposure Database available on GitHub (US data soon)

- Main takeaways:
  1. Overall positive impact on US employment with substantial heterogeneity by worker types
  2. Reskilling and upskilling policies for vulnerable workers are necessary, particularly those in core working-age groups and with lower education levels

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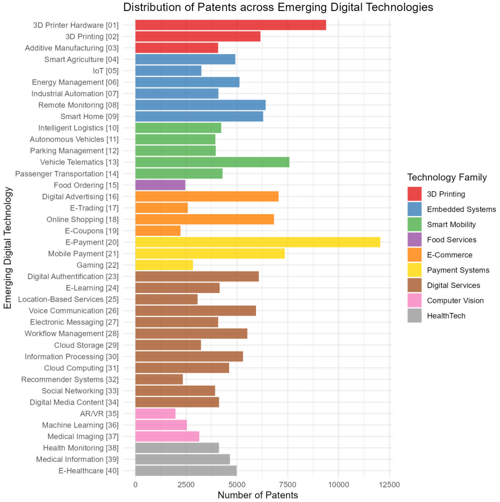
Some Examples of Patents

◀ 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



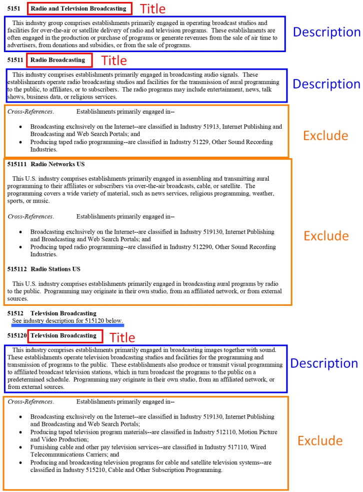
NAICS Industry Classification (4-digit level)

◂ Go back

- 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 $s \in S_i$

- This results in 324 industries at the 4-digit level, each represented by 4.5 composite sentences on average



5151 Radio and Television Broadcasting

This industry group comprises establishments primarily engaged in operating broadcast studios and facilities for over-the-air or satellite delivery of radio and television programs. These establishments are often engaged in the production or purchase of programs or generate revenues from the sale of air time to advertisers, from donations and subsidies, or from the sale of programs.

51511 Radio Broadcasting

This industry comprises establishments primarily engaged in broadcasting audio signals. These establishments operate radio broadcasting studios and facilities for the transmission of aural programming to the public, to affiliates, or to subscribers. The radio programs may include entertainment, news, talk shows, business data, or religious services.

Cross-References. Establishments primarily engaged in--

- Broadcasting exclusively on the Internet--are classified in Industry 51913, Internet Publishing and Broadcasting and Web Search Portals; and
- Producing taped radio programming--are classified in Industry 51229, Other Sound Recording Industries.

515111 Radio Networks US

This U.S. industry comprises establishments primarily engaged in assembling and transmitting aural programming to their affiliates or subscribers via over-the-air broadcasts, cable, or satellite. The programming covers a wide variety of material, such as news services, religious programming, weather, sports, or music.

Cross-References. Establishments primarily engaged in--

- Broadcasting exclusively on the Internet--are classified in Industry 519130, Internet Publishing and Broadcasting and Web Search Portals; and
- Producing taped radio programming--are classified in Industry 512290, Other Sound Recording Industries.

515112 Radio Stations US

This U.S. industry comprises establishments primarily engaged in broadcasting aural programs by radio to the public. Programming may originate in their own studio, from an affiliated network, or from external sources.

51512 Television Broadcasting

See industry description for 515120 below.

515120 Television Broadcasting

This industry comprises establishments primarily engaged in broadcasting images together with sound. These establishments operate television broadcasting studios and facilities for the programming and transmission of programs to the public. These establishments also produce or transmit visual programming to affiliated broadcast television stations, which in turn broadcast the programs to the public on a predetermined schedule. Programming may originate in their own studio, from an affiliated network, or from external sources.

Cross-References. Establishments primarily engaged in--

- Broadcasting exclusively on the Internet--are classified in Industry 519130, Internet Publishing and Broadcasting and Web Search Portals;
- Producing taped television program materials--are classified in Industry 512110, Motion Picture and Video Production;
- Furnishing cable and other pay television services--are classified in Industry 517110, Wired Telecommunications Carriers; and
- Producing and broadcasting television programs for cable and satellite television systems--are classified in Industry 515210, Cable and Other Subscription Programming.

Embeddings and Cosine Similarity Scores

Go back

- 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:

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

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

$$C_i^{p_1} := \arg\max_{s \in S_i} C_{s,i}^{p_1} \qquad \text{and} \qquad C_i^{p_2} := \arg\max_{s \in S_i} C_{s,i}^{p_2}$$

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:

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

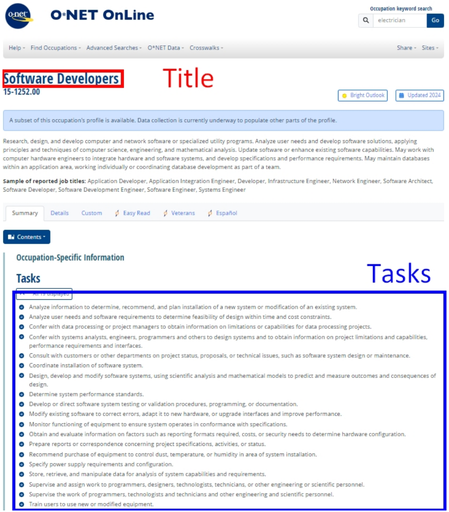
$\Rightarrow$ We establish a (semantic) connection between an invention p and a set of relevant industries $i \in \mathcal{I}$

Cosine Similarity for Occupations: Summary

◂ Go back

- We use the SOC Classification (at the 6-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 $o \in \mathcal{O}$



Weighting Scheme

◂ Go back

- The weight assigned to a patent p is:

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

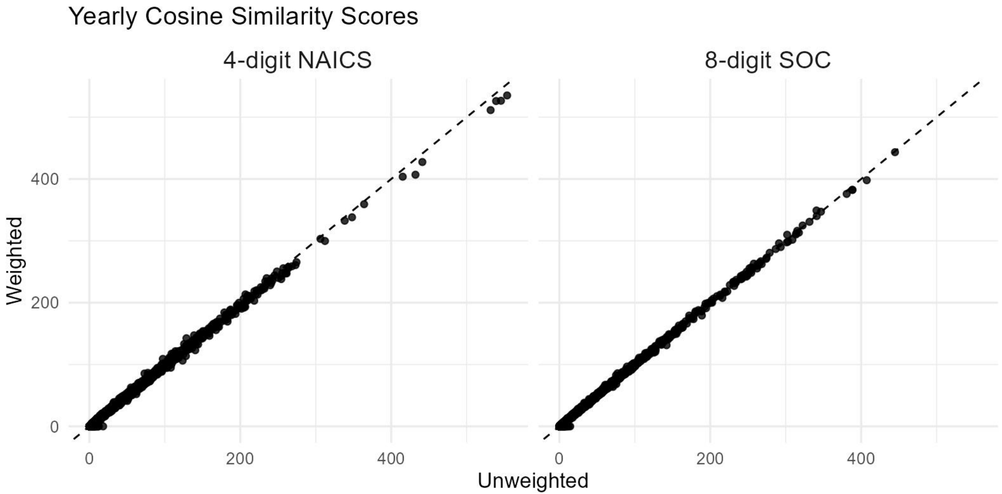
  - m_p is the number of citations received by patent p
  - $\mathcal{P}_{dt}^k$ is the set of patents belonging to emerging digital technology k, filed in year t, and relevant to industry/occupation $d = \{i, o\}$

- 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



Average Employment Share by Industry in 2010 (in percent)

Go back

	NAICS Industry	Emp. Share Mean	Emp. Share SD	Shock
11	Agriculture, Forestry, Fishing and Hunting	1.4	4.1	0.3
21	Mining, Quarrying, and Oil and Gas Extraction	0.5	2.1	0.2
22	Utilities	0.9	0.1	1.2
23	Construction	7.1	2.1	1.0
31-33	Manufacturing	11.0	23.1	2.8
41	Wholesale Trade	3.0	0.4	1.9
44-45	Retail Trade	11.5	1.4	2.2
48-49	Transportation and Warehousing	4.2	1.1	2.2
51	Information and Cultural Industries	2.3	0.6	3.7
52	Finance and Insurance	4.9	2.9	1.9
53	Real Estate and Rental and Leasing	2.0	0.4	2.5
54	Professional, Scientific and Technical Services	6.2	6.9	3.2
55	Management of Companies and Enterprises	0.1	0.0	0.7
56	Administrative and Support, Waste Management and Remediation Services	4.0	0.7	3.2
61	Educational Services	9.2	3.6	1.7
62	Health Care and Social Assistance	12.9	4.4	1.2
71	Arts, Entertainment and Recreation	2.0	0.9	0.9
72	Accommodation and Food Services	6.8	2.1	1.7
81	Other Services (except Public Administration)	4.9	0.3	1.9
91	Public Administration	4.9	4.6	0.6

Notes: This table presents the average employment shares in 2010 by 2-digit NAICS industry, which is averaged across all the CZs, and the average exposure to digital technologies which is the shock in the shift-share. CZs are weighted by population in 2010. The first column indicates the 2-digit NAICS codes, the second column is the name of the NAICS industry, the third column is the average employment share in 2010, the fourth column gives the standard deviation (SD), and the fifth column corresponds to the industry exposure to digital technologies.

References I

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

Autor, D., Chin, C., Salomons, A., and Seegmiller, B. (2024). New Frontiers: The Origins and Content of New Work, 19402018. *The Quarterly Journal of Economics*, 139(3):1399–1465.

Bonfiglioli, A., Crinò, R., Gancia, G., and Papadakis, I. (2024). Artificial Intelligence and Jobs: Evidence from US Commuting Zones. *Economic Policy*, 40(121):145–194.

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.

Dorn, D. (2009). *Essays on Inequality, Spatial Interaction, and the Demand for Skills*. PhD thesis, University of St. Gallen.

References II

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.

Felten, E. W., Raj, M., and Seamans, R. (2018). A Method to Link Advances in Artificial Intelligence to Occupational Abilities. *AEA Papers and Proceedings*, 108:54–57.

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.

Hampole, M., Papanikolaou, D., Schmidt, L. D. W., and Seegmiller, B. (2025). Artificial intelligence and the labor market. Working Paper w33509, National Bureau of Economic Research.

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.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, 132:665–712.

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

References III

Prytkova, E., Petit, F., Li, D., Chaturvedi, S., and Ciarli, T. (2024). The Employment Impact of Emerging Digital Technologies. Working Paper.

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.

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