Impact of Automation and Augmentation Technologies on Employment in Europe

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Motivation

- Automation may disrupt labor markets:
  - Displacement (*automation*) effect
  - Reinstatement (*augmentation*) effect
- The net effect on employment is an empirical question (Arntz et al. (2019))
- Literature considering both effects simultaneously is scarce (Autor et al. (2024) QJE)
- Europe is not in the scope of interest. Why?

  ... we apply existing ideas not transferring previous results to the European context.

Implementation

- We identify what tasks humans and technology perform ...and measure to what extent these input tasks overlap (*automation*).
- We identify what is the final output that technology potentially complements
  ... and measure how the final output and technology are 'close' to each other (*augmentation*).

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Data

- *On the workers side:* Description of task in the cleaned description of tasks based on ISCO-08 by Mihaylov and Tijdens (2019) and occupational microtitles by Tijdens (2023) and merged EU-LFS since 1993 to 2017 for Germany, the United Kingdom, France, Italy, and Spain
- *On the technology side:* Google Patents Public database

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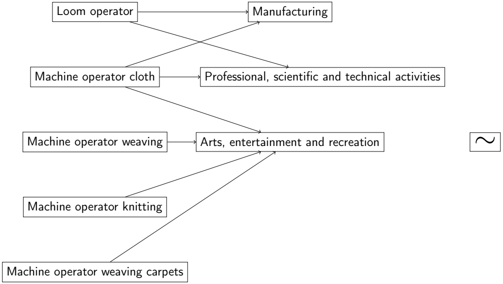
What labor is actually doing? ... The technology may substitute for.

Weawing and Knitting Machine Operators - Unit Group 8152 ISCO 08: Setting up and operating batteries of automatic, link-type knitting machines to knit garments of specified pattern and design, Threading yarn, thread and fabric through guides, needles and rollers of machines for weaving, knitting or other processing...

Electrical Engineers - Unit Group 2151 ISCO 08: Advising on and designing power stations and systems which generate, transmit and distribute electrical power, Supervising, controlling and monitoring the operation of electrical generation, transmission and distribution systems, Advising on and designing systems for electrical motors, electrical traction...

But what is the output of an occupation that technology could complement?



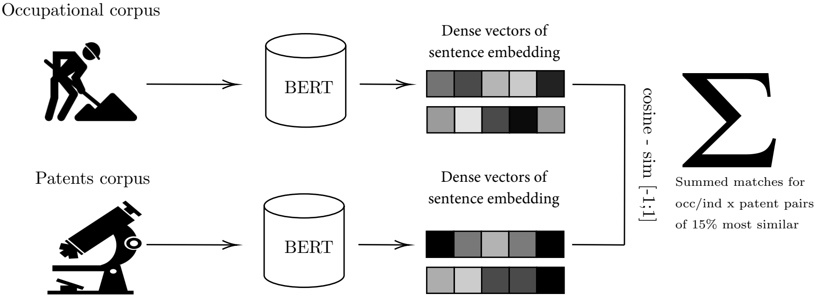
JP-H05140844-A Prediction system and control unit for malweaving in loom: AI
JP-2005095696-A Computerized sewing machine: software
CN-104420075-A Electro-pattern-sewing machine: robots
CN-101177848-A Direct-driving single needle industrial sewing machine control system: software
JP-2020195650-A Sewing system: robots
CN-104345689-A Self-calibration control device of warp knitting machine yarn guide bar: software
CN-111401629-A Production management algorithm and production management method for warp knitting workshop of intelligent knitting factory: software
JP-H05245283-A Needle thread feed quantity control device for sewing machine: robots

Scheme of micro-occupational titles obtained from Tijdens (2023) database - for Weaving and Knitting Machine Operators - Unit Group 8151, that with industries (NACE Rev. 2 one-digit) could form these combinations of occupation-industry pairs. An example of patents' titles and respective technology that could augment these occupation-industry pairs.

What technology is capable of substituting and complementing?

- Technological advances is measured by patents (Mann and Püttmann (2018); Webb (2019); Dechezleprêtre et al. (2021); Autor et al. (2024)).
- Beside of technological advancement as a whole (main analysis), we used a dictionary-based labels of a broad technological category of each technology to robots, software, and AI (robustness check)(not exclusively distinct subset).
- Extracting the meaning of description in patent titles and abstracts for each technology.

Our measure of European-specific automation and augmentation exposure

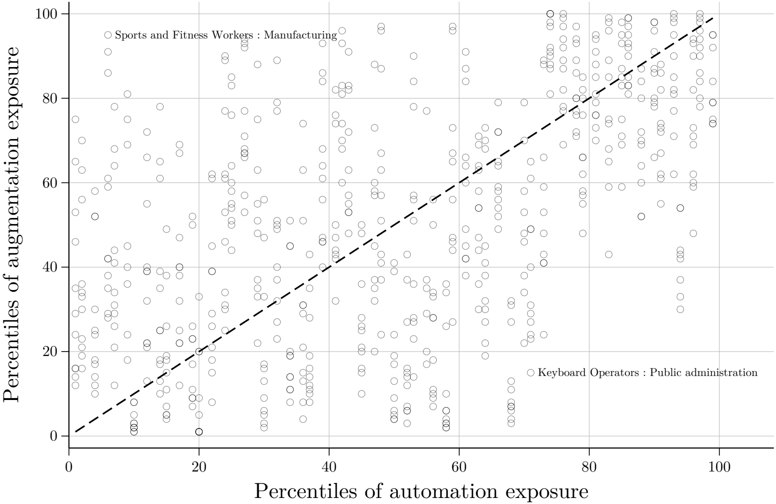


Adapted process of creation augmentation/automation exposure of occupational tasks in ISCO-08 from Autor et al. (2024). Sentence embeddings are obtained by BERT-for-patents model, fine-tuned on the entire Google patent database by Srebrovic and Yonamine (2020).

$$I_{p,j} = 1 \text{ if } X_{p,j} \geq \lambda_t \text{ and zero otherwise;}$$

$$Aut_t = \sum_{p \in \mathcal{P}} \sum_{j \in \mathcal{O}} I_{p,j}$$

Average exposure to automation and augmentation technologies in Europe



Empirical specification

$$100 \times \ln(\Delta E_{ij,t}) = \beta_1 AugX_{ij} + \beta_2 AutX_{j,t} + \gamma_{i,t} + \delta_{j,t} + \varepsilon_{ij,t}$$

$100 \times \ln(\Delta E_{ij,t})$: five-year stacked long-run difference in the total full-time equivalent employment[1] in the consistent one-digit NACE r.2 industry i by three-digit ISCO-08 occupation j cell[2]

$AugX_{ij,t}$: IHS transformed augmentation exposure in the industry-by-occupation cells

$AutX_{j,t}$ IHS transformed automation exposure in the occupation cells by to technology as a whole and to subset of each respective technology (robots, software, and AI).

$\gamma_{i,t}; \delta_{j,t}$: fixed effects

Testable hypotheses: $\beta_1 > 0$ $\beta_2 < 0$

[1] *hwusual* and divide by 35.

[2] Crosswalking industries (NACE Rev. 1.1 to NACE Rev. 2) and occupations (ISCO 88 to ISCO 08) and retaining only unambiguously matched occupations

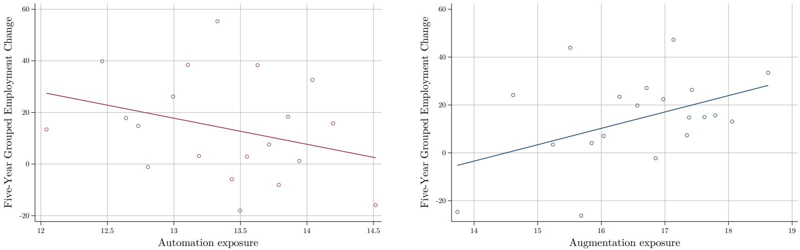


Figure: Conditional Correlations between Automation, Augmentation Exposure and Five-Year Groups Employment Change.

Not all innovations were created equal...

- Two similarity measures are computed inspired by Kelly et al. (2021) AER:
  - **Backward Similarity (B-SIM)**: Average similarity between the patent p and patents granted in the five years prior:

$$\text{B-SIM}(p,t) = \frac{1}{N_b} \sum_{j=-1}^{-5} \sum_{i=1}^{N_{b_j}} \text{sim}(p, p_{i,j}^{\text{prior}}) \tag{1}$$

  - **Forward Similarity (F-SIM)**: Average similarity between the patent p and patents granted in the five years following:

$$\text{F-SIM}(p,t) = \frac{1}{N_f} \sum_{j=1}^{5} \sum_{i=1}^{N_{f_j}} \text{sim}(p, p_{i,j}^{\text{forward}}) \tag{2}$$

- A patent is classified as a breakthrough if:

$$\text{Breakthrough}(p) = \begin{cases} 1 & \text{if } \frac{\text{F-SIM}(p)}{\text{B-SIM}(p)} \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Evolution of innovations' quality over time

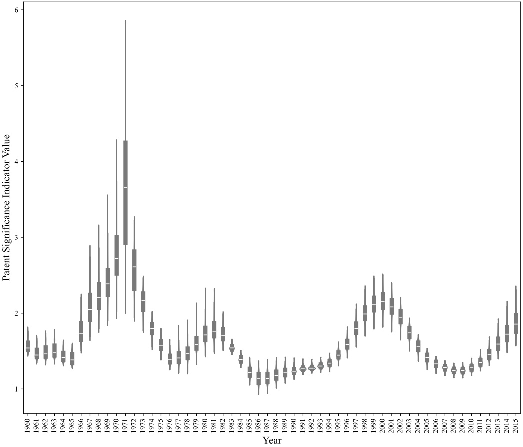


Figure: Patent significance (1960-2010) based on Forward and Backward Similarity inspired by Kelly et al. (2021).

	100 × Five-year grouped Δ(Employment)	
	All innovations	
	(1)	(2)
Augmentation exposure	12.73**	11.63**
	(5.09)	(5.78)
Automation exposure	-12.41**	-15.09*
	(6.04)	(7.79)
	Breakthrough innovations	
	(1)	(2)
Augmentation exposure	13.45***	13.00**
	(5.03)	(5.93)
Automation exposure	-12.81**	-13.47*
	(6.35)	(7.75)
N	4102	4102
R^2	0.06	0.13
Industry × Time FE	Yes	Yes
Broad Occupations × Time FE	No	Yes

Table: Changes in employment in consistently defined occupation-industry cells in the EU-LFS over 1993-2018. Employment changes are winsorized on the top and bottom one percentile. Augmentation and automation exposures measure correspond to the inverse hyperbolic sine (IHS) of aggregated patents. Observations are weighted by mean employment for each occupation-industry cell across the whole time period. Standard errors in parentheses are clustered by industry-occupation cell. $p^* < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

	100 × *Five-year grouped* Δ(*Employment*)			
	All innovations			
	Manufacturing		Non-manufacturing	
	(1)	(2)	(3)	(4)
Augmentation exposure	10.72	11.36**	13.13**	11.60***
	(7.94)	(4.78)	(5.98)	(2.06)
Automation exposure	-7.18	-10.74**	-14.55**	-16.89***
	(10.81)	(5.12)	(7.18)	(3.22)
	Breakthrough innovations			
Augmentation exposure	12.23*	14.57***	13.67**	12.76***
	(6.90)	(4.65)	(6.06)	(2.10)
Automation exposure	-7.08	-11.33**	-15.17**	-14.66***
	(11.15)	(5.12)	(7.63)	(3.38)
N	1032	1032	3070	3070
R^2	0.07	0.14	0.07	0.14
Industry × Time FE	Yes	Yes	Yes	Yes
Broad Occupations × Time FE	No	Yes	No	Yes

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	100 × *Five-year grouped* Δ(*Employment*)	
	All innovations	
	(1)	(2)
Augmentation exposure	11.69**	9.70*
	(4.98)	(5.61)
Automation exposure	-11.85*	-13.15
	(6.45)	(8.16)
N	4102	4102
Hansen J statistics	0.00	0.00
Industry × Time FE	Yes	Yes
Broad Occupations × Time FE	No	Yes

Table: The Relationship between Changes in Employment and Exposure to Augmentation and Automation by All Technologies within Industry-Occupation Cells, 2SLS Stacked Long-Difference Regressions, 1993–2018. Standard errors in parentheses are clustered by industry-occupation cell. $p^{*} < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

The size of reinstatement and replacement of labor in Europe by each technology

	Robot		Software		AI	
	(1)	(2)	(3)	(4)	(5)	(6)
	100 × Five-year grouped Δ(Employment)					
Augmentation exposure	6.45**	$4.21^{\dagger}$	8.70***	$6.16^{\dagger}$	7.75***	6.55*
	(2.99)	(3.03)	(3.04)	(3.76)	(2.85)	(3.81)
Automation exposure	-2.84	-11.81**	-2.95	-13.04**	-6.97*	-15.73***
	(4.16)	(5.61)	(4.30)	(6.62)	(4.03)	(5.66)
N	2389	2389	2389	2389	2389	2389
R^2	0.34	0.65	0.35	0.65	0.35	0.66
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Broad Occupations × Time FE	No	Yes	No	Yes	No	Yes

Table: Changes in employment in consistently defined occupation-industry cells in the EU-LFS over 1993-2018. Augmentation and augmentation exposure measures correspond to the inverse hyperbolic sine (IHS) of matched patents for each technology. Weighted by start-of-period employment for each occupation-industry cell. SE are clustered by industry-occupation cell. $p^{\dagger} < 0.20$, $p^{*} < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

Conclusions

- We create a new measure of automation exposure and augmentation exposure scores for ISCO 08 occupations based on Autor et al. (2024).
- Results obtained for the European labor market are in line with Autor et al. (2024) conceptual framework and results obtained in the US.
- Occupations more exposed to automation technologies are also more exposed to augmentation technologies.
- Both exposures have a presumed effect on the replacement and reinstatement of labor across ind-occupation cells.
- Future work: proper IV identification of downstream automation and augmentation patents resulting from breakthrough innovations.

Thank you for your attention!

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