EUROPEAN CENTRAL BANK

EUROSYSTEM

New technologies and jobs in Europe

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Motivation

- A new wave of digital technological developments has emerged since approximately 2010. Characterized by **artificial intelligence (AI) breakthroughs**

- These are deep learning and machine learning applications based on algorithms that learn to perform tasks by following **statistical patterns in data**, rather than following human instructions

- E.g. supervised and unsupervised learning, natural language processing, or image recognition among many other activities

- AI is experiencing fast growth and diffusion, the most recent development being **Generative AI**, such as ChatGPT, that uses deep learning techniques to generate new content, such as images, music, and text.

Motivation

- Waves of automation have usually been accompanied by concerns about the future of jobs.

- This apprehension persists, even though history suggests that previous fears about labour becoming substituted by machines have been exaggerated (e.g. Autor (2015), Bessen (2019)).

Motivation

What is new about AI?

- AI is a general-purpose technology that enables automation of human labour in **non-routine tasks**, both in manufacturing but also services (e.g. medical advice or writing code).

- In contrast, computerisation and industrial robots enable automation in a limited set of tasks by implementing **manually-specified rules.**

- AI is often embedded in robots/computers.

Motivation

- New AI technologies trigger **old concerns** about their labour market consequences.

  – What is its impact on employment and wages?
  – Does AI replace workers, complement them or generate demand for new jobs?
  – Are its effects different across workers/occupations by education and age?

- Thus, the debate about the **potential impact of technologies on jobs** has been revived (see for example Ford (2015), Frey and Osborne (2017), Susskind (2020) and Acemoglu and Restrepo (2020b)).

Literature

The two leading theories explaining the **main transmission mechanisms of technological changes on labour market outcomes** highlight a heterogeneous impact of technology on workers with different skills.

1. **Skill Biased Technological Change (SBTC)**
   - New technologies substitute low skill work and complement high skill work
   - SBTC explains the initial source of the rise in inequality that started in the late 1970s
   - Katz y Murphy (1992), Autor et al. (1998), Autor y Katz (1999), etc.

2. **Routinisation**
   - Middle-skilled workers in routine intensive jobs, were displaced due to computerisation.
   - Routinisation explains that in the early 90's wage and job polarisation accelerated.
   - Goos y Manning (2007), Acemoglu y Autor (2011), Autor y Dorn (2013), (Autor, 2015), etc.

This paper

- This paper contributes to the literature exploring the links between AI-enabled technologies and labour market outcomes in 16 European countries over the period 2011-2019.

- These years saw the rise of **deep learning applications**. Those are more limited in scope than the current generative AI models, but still revolutionary, and still trigger concerns about the impact on jobs.

- We use data at 3-digit occupation level (according to the International Standard Classification of Occupations, ISCO) from the Eurostat's Labour Force Survey and two proxies of potential AI-enabled automation, borrowed from the literature.

Technology data

Two proxies of potential AI-enabled automation, borrowed from the literature

1. **Exposure of tasks and occupations to AI, Webb (2020)**

- Quantify textual overlap (verb-noun pairs) of:
  - **Patents description** taken from Google Patent Public Data
  - Jobs descriptions from **O*Net**, a survey which asks a random sample of U.S. workers in each occupation about **typical work activities** required in their occupations.

chart

Technology data

2. AI Occupational Impact scores (AIOI), Felten et al (2019)

- Quantify the link between :

  – **Advances in various AI applications** (image and speech recog., translation, abstract strategy games, etc.) as reported by the *Electronic Frontier Foundation (EEF).*

  – **2019 O*NET** 52 distinct abilities and information on the prevalence and importance of each ability per occupation.

  – They rely on *mTurk* survey responses to construct a matrix connecting the EEF AI Progress measures to the O*NET occupation-level ability data.

Technology data

- These AI measures differ in the way they capture the applicability of AI to a task.
  - Felten et al. is driven by the exposure of workers’ abilities to technological advancements,
  - Webb highlights the availability of machine learning algorithms that are aligned with occupations’ tasks

- Both AI measures indicate **the potentiality** of AI impact on given occupations, rather than materialised AI impact

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Labor data

- Micro-data on **employment and wages** from the EU-LFS (Labour Force Survey) uses the ISCO classification system

- EU-LFS individual data allows us to construct **employment shares and relative wages** at ISCO 3 digits-occupation levels

- **Individual and occupation specific features:** demographics, skill distribution, structural factors affecting labour supply (gender, age, etc). Also available from LFS and aggregated at 3-digits occupation level, ISCO-08 classification .

Merged database for Europe

- **Unit of analysis:** occupations at 3-digits **ISCO-08** classification x sector.

- Technology measures from US generally provided for occupations classified in the Standard Occupational Classification (**SOC**) system, which is a US federal statistical standard.

- We merge occupation classifications using crosswalks and correspondence tables from Hardy et al. (2018), U.S. Bureau of Labor Statistics (2012), ILO (2010), and also manually match some remaining occupations. SOC2010 (6 or 8 digits) →ISCO-08 (3 digits).

- Implicit assumption: tasks are equally exposed to technology in the EU countries than in the US.

Agenda for the rest of the talk

Relationship between the proxies of technology exposure and **changes in employment shares/ changes in relative wages** by cells (sectors x occupations)

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Relationship between the proxies of technology exposure and **changes in employment shares/ changes in relative wages** by cells (sectors x occupations)

aggregate (pooled sample)
along the skill and age distribution
across countries

Empirical approach

$$y_{so,c} = \alpha_c + \alpha_s + \beta_c X_{so,c} + \epsilon_{so,c}$$

- Unit of **observation** is an occupation-sector-country **cell** (*so*), 16 countries (*c*):
- *Y*: dependent variable
  - **Change in the employment share** of sector–occupation (*so*) in country *c* from 2011 to 2019.
  - **Change in the wage distribution** position of sector-occupation *so* in country *c* also from 2011 to 2019
- *X*: **percentiles** of potential exposure of the sector-occupation-country units to AI
- β**: parameter of interest.** Negative (positive) indicates that potentially more automated sector-occupations had declining (increasing) employment shares or relative wages.

Potential results

Depending on the sign of the βc coefficients in the employment and wage equations, the relationship between technologies and jobs can be understood as being one of complementarity, displacement, or both

- **Complementarity:** more automation is associated with increases in both employment shares and relative wages / productivity.
- **Displacement:** both coefficients negative /substitution.
- **Reinstatement:** some tasks or jobs are destroyed but new ones are created within the same occupation-sector cell.

Results

aggregate (pooled sample)
along the skill and age distribution
across countries

Results

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Employment. Results

Table B1: Change in employment vs. exposure to technology. Pooled sample. 2011-2019.

	(1)	(2)	(3)	(4)	(5)
AI, Webb	0.104***	0.111***			0.192***
	(0.027)	(0.027)			(0.037)
AI,Webb.Unweigthed			0.099***	0.106***	
			(0.029)	(0.029)	
Software Exp					-0.143***
					(0.036)
Observations	6767	6767	6767	6767	6767
AI, Felten	0.174***	0.174***			0.175***
	(0.034)	(0.034)			(0.036)
AI,Felten.Unweigthed			0.175***	0.176***	
			(0.034)	(0.034)	
Software Exp					0.015
					(0.031)
Observations	5766	5766	5766	5766	5750

Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. AI variables in columns (1), (2) and (5) are 2011 employment weighted percentiles of AI scores, columns (3) and (4) show the results for unweighted pecentiles of AI scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included. Columns (5) as (1) plus the Software exposure measure as in Webb (2019).

- **Positive association** between AI enabled automation and changes in employment shares in the pooled sample.
- I.e. Occupations (potentially) more exposed to AI increased their employment in the period 2011-19.
- This is the case regardless of the indicator of exposure to AI used to proxy AI enabled automation.

Employment. Results

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- **AI exposure indicator by Webb:** on average in Europe, moving 10 centiles up (e.g. from centile 30 to 40) along the distribution of exposure to AI is associated with an increase of sector-occupation employment share of 1.04%.

- **Measure provided by Felten et al.:** the estimated increase of sector-occupation employment share is 1.74%.

Employment. Role of sector and **occupation groups**

Table B5: Change in employment vs exposure to AI. 2011-2019. Occupations

	(All)	(1)	(2)	(3)	(4	(5)	(6)	(7)	(8)	(9)
AI, Webb	0.104***	0.118***	0.011	0.116***	0.069**	0.117***	0.118***	0.114***	0.122***	0.120***
	(0.027)	(0.027)	(0.030)	(0.030)	(0.029)	(0.030)	(0.028)	(0.028)	(0.030)	(0.031)
Observations	6767	6113	5354	5621	6203	6101	6560	5877	6093	6214
AI, Felten	0.174***	0.195***	0.050	0.196***	0.170***	0.200***	0.169***	0.151***	0.174***	0.225***
	(0.034)	(0.035)	(0.042)	(0.034)	(0.034)	(0.033)	(0.034)	(0.037)	(0.034)	(0.041)
Observations	5766	5165	4559	4630	5579	5204	5557	4876	5302	5256

Notes: See notes for column (1) in Table B1. Column named (All) includes the whole sample. The rest of the columns exclude occupations in one of ISCO major groups. Column named (1) excludes managers; (2) excludes professional; (3) excludes technicians; (4) excludes clerical support workers; (5) services and sales workers ; (6) skill agriculture, forestry and fishing; (7) craft workers; (8) plant and machine operators (9) elementary occupations.

- Table B5 presents the result of sequentially excluding those 3-digit ISCO-08 occupations that can be grouped in each ISCO-08 major group (1-digit code level groups).
- The occupation group *Professionals* (ISCO-08 major group 2) seem to be driving our results.
- This group consists of occupations whose main tasks require a **high level of professional knowledge** and experience in the fields of physical and life sciences, or social sciences and humanities.

Employment. Role of **sector** and occupation groups

Table B3: Changes in employment vs. exposure to AI. 2011-2019. Sectors.

	(All)	(1)	(2)	(3)	(4)	(5)	(6)
AI, Webb	0.104***	0.112***	0.101***	0.090***	0.113***	0.092***	0.135***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.029)	(0.032)	(0.040)
Observations	6767	6106	5877	6133	5403	5257	5059
AI, Felten	0.174***	0.169***	0.162***	0.166***	0.184***	0.159***	0.233***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.039)	(0.040)	(0.036)
Observations	5766	5189	4994	5247	4628	4476	4296

Notes: See notes for column (1) in Table B1. Column named (All) includes the whole sample. The rest of the columns exclude one sector. Column named (1) excludes agriculture; (2) excludes construction; (3) excludes financial services; (4) excludes services; (5) excludes manufacturing and (6) excludes public services.

- Table B4 presents the result of sequentially excluding sectors.
- None of the 6 sectors appears to be driving the positive relationship between employment and AI exposure

Wages. Results

Complementarity?/ Reinstatement?

Table B2: Relative wage changes vs. exposure to AI. Pooled sample 2011-2019

	(1)	(2)	(3)	(4)	(5)
AI, Webb	0.001	0.001			-0.003
	(0.006)	(0.006)			(0.008)
AI,Webb.Unweighted			0.001	0.001	
			(0.006)	(0.006)	
Software Exp					0.008
					(0.008)
Observations	5729	5729	5733	5733	5729
AI, Felten	-0.013*	-0.011			-0.011
	(0.008)	(0.008)			(0.008)
AI,Felten.Unweighted			-0.013	-0.012	
			(0.008)	(0.008)	
Software Exp					0.003
					(0.007)
Observations	4872	4872	4875	4875	4866

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Dependent variable: within country cell's change in relative wages from 2011 to 2019 winsorised 1 percent top and bottom. Due to limited data availability for the reference years, 2018 wages values were taken for AT, ES and LT, and 2017 for FI instead of 2019. For the UK 2013 wages were taken instead of 2011. AI variables in columns (1), (2) and (5) are 2011 employment weighted percentiles of AI scores, columns (3) and (4) show the results for unweighted pecentiles of AI scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included. Columns (5) as (1) plus the Software exposure measure as in Webb (2019).

Comparing to US

- Our results stand in some contrast with those found for the US

- For example, both Felten et al. (2019) and Acemoglu et al. (2022) conclude that occupations more exposed to AI experience no visible impact on employment.

- However, Acemoglu et al.(2022) find that AI-exposed establishments reduced non-AI and overall hiring, implying that AI is substituting human labour in a subset of tasks, while new tasks are created.

- Bonfiglioli, at al (2024) find negative effects of AI on employment for low skill workers and positive for workers at the top of the wage distribution. These results are consistent with widening of inequality.

Results

aggregate (pooled sample)

along the skill and age distribution

across countries

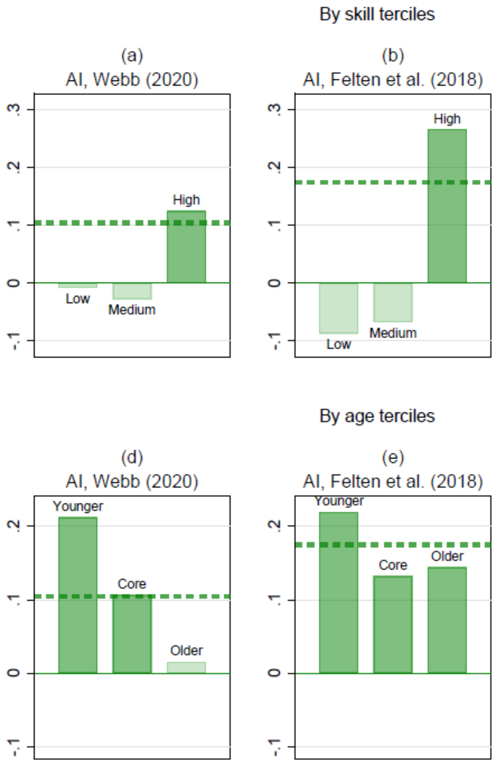
Skill and age distribution

- We rank the sector-occupation cells within each country by age and skills terciles in 2011, the initial year of our sample.

- The first **age tercile** includes those observations (sector-occupation cells) whose average age was in the lower tercile of the country’s age distribution in 2011.

- The first **skill tercile** consists of these sector-occupation cells whose average educational attainment is in the lower tercile of country’s education distribution in 2011.

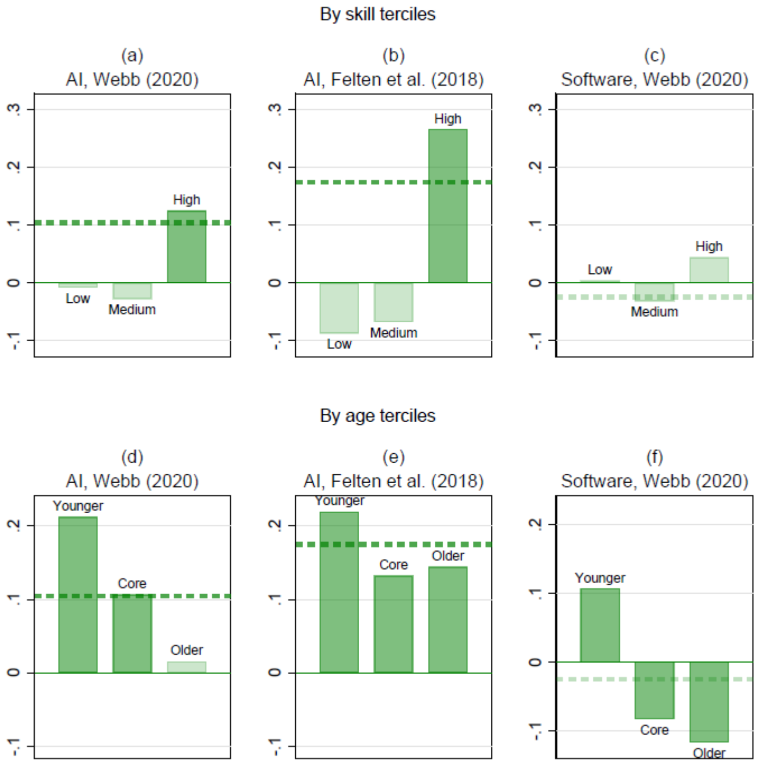
Results by age and skills



Notes: Regression coefficients measuring the effect of exposure to technology on changes in employment share. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells average labour supply. Sector and country dummies included. Sample: 16 European countries, 2011 to 2019.

- Occupations potentially more exposed to AI-enabled technologies increased their employment share.
- This has been particularly the case for occupations with a relatively higher proportion of **younger and skilled** workers.

Results by age and skills



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- Occupations potentially more exposed to AI-enabled technologies increased their employment share.
- This has been particularly the case for occupations with a relatively higher proportion of **younger and skilled** workers.
- In contrast, we do not identify for Europe a remarkable impact of software on employment shares for the period of analysis.

Results

aggregate (pooled sample)

along the skill and age distribution

across countries

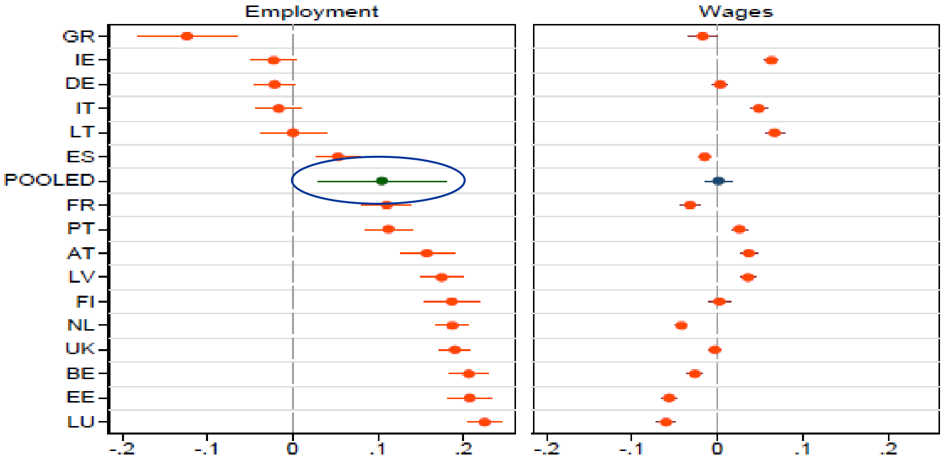
Country results

- Employment: while there is **heterogeneity in the magnitude** of the estimates, **the positive sign** of the relationship between AI-enabled automation and employment shares also holds at the country level with only a few exceptions.

- Regarding wages in most of the countries the statistical association of changes in relative wages and AI measures **is zero or negative**

Country results (Webb)

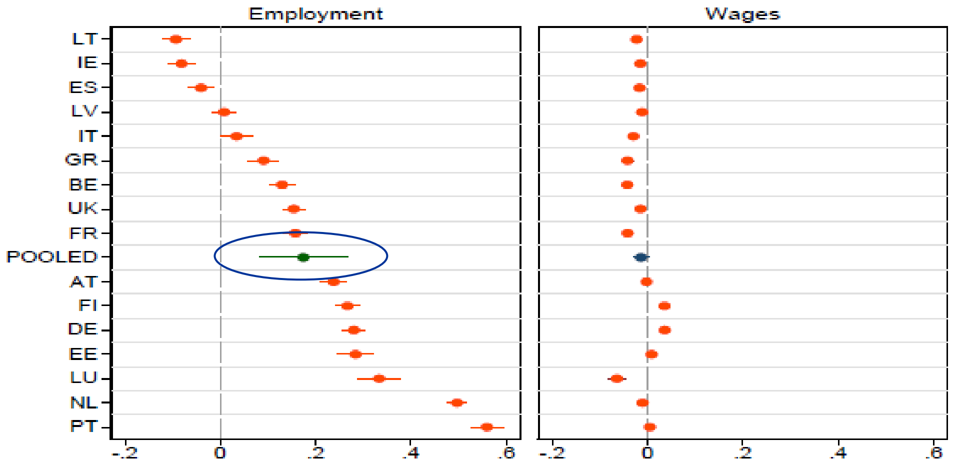
Figure 6: Exposure to AI, Webb, and changes in employment shares and wage percentiles, by countries



Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B7 and B8.

Country results (Felten)

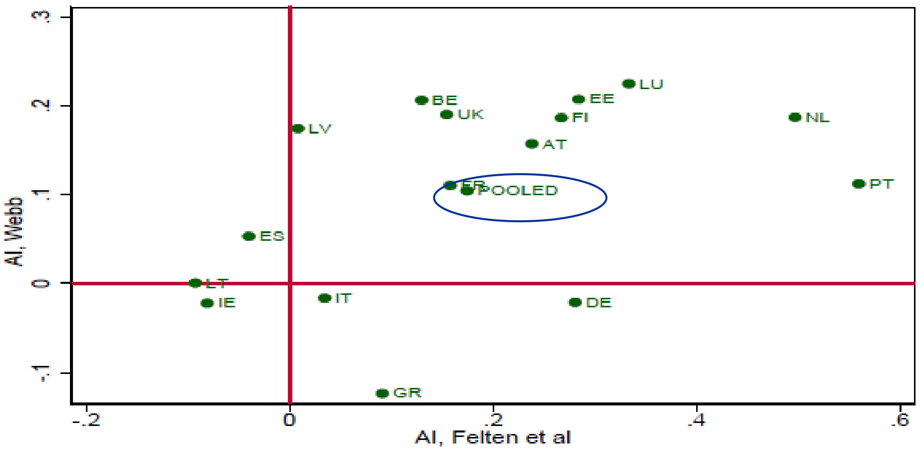
Figure 7: Exposure to AI, Felten at al, and changes in employment shares and wage percentiles, by countries



Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B9 and B10.

Country results (both)

Figure 8: Exposure to AI, Webb and Felten et al., and changes in employment shares, by country



Notes: Scatter plot of regression coefficients measuring the effect of exposure to AI on changes in employment share. X-axis: regression coefficients using the AI proxy based on Felten et al. Y-axis: regression coefficients using the AI proxy based on Webb. For further details see notes to Figure 5.

Interpreting country heterogeneity

Table 5: Correlations between country estimates and institutions

	AI (Webb)	AI (Felten et al.)	Software (Webb)
Digital Economy and Society Index	.40	0.42	-0.08
Employment Protection Legislation	-0.08	-0.17	-0.33
Product Market Regulations	-0.50	-0.30	-0.12
Pisa score	0.30	0.32	0.20
Share of tertiary education	0.31	0.24	-0.22

Notes: Spearman's rank correlations. DESI includes human capital, connectivity, integration of digital technology and digital public services.

Conclusions

1. AI enabled automation in Europe is associated with employment increases while the relationship with wages is statistically not significant or negative and hardly significant.

2. The positive association with employment increases is driven by occupations with relatively higher proportion of skilled workers, which is in line with the SBTC theory.

3. The positive relationship employment/AI enabled automation **holds across countries** with only a few exceptions. However, there is remarkable heterogeneity in the magnitude of the coefficients.

4. This heterogeneity across countries, possibly reflects different economics structures such as pace of technology diffusion and education, but also product market regulation and employment.

A note of caution

AI-enabled technologies continue to be developed and adopted and most of their impact on employment and wages are yet to be realised. While in the period of our analysis the association is positive, these results may not be extrapolated into the future.

Thank you