Discussion:

‘New Technologies and Jobs in Europe’

by Albanesi, Dias da Silva, Jimeno, Lamo & Wabitsch

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Summary

Main findings:

1. Employment shares in Europe rose by more over 2011-19 in occupations that were more exposed to AI
2. Especially for:
   i Occupations with younger and more skilled workers
   ii Countries closer to tech frontier, with more competitive product markets, more flexible labor markets, and higher educational attainment

My view:

1. Important topic, new cross-country perspective, carefully executed
2. Comments focus on extending the analysis

Relationship to the literature

AI Exposure $\longrightarrow$ **AI Adoption** $\longrightarrow$ **Employment**

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(Pre-GenAI ML; not exhaustive)

AI Exposure → **AI Adoption** → **Employment**

Measure at task level:

Felten et al. (2018)

Brynjolfsson et al. (2018)

Webb (2020)

Pizzinelli et al. (2023)

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Predictive?

+ Acemoglu et al. (2022, US)

+ Copestake et al. (2023, India)

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Impact within establishments:

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Impact within regions:

— Bonfiglioli et al. (2023, US)

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Relationship across occupations:

∼ Felten et al. (2019, US 2010-16)

∼ Acemoglu et al. (2022, US 2010-18)

\+ **Albanesi et al. (2024, 16 European countries 2011-19)**

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⇒ Significant positive relationship in Europe—how to interpret?

1. Results: unpack role of professionals

Table C3: 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.

- Results driven by 1-digit occupation group *Professionals*
  - ⇒ Explore at 2-digit level (driven by *Engineering/Heath/Teaching/Business* etc.?)

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- Results driven by 1-digit occupation group *Professionals*
  - ⟹ Explore at 2-digit level (driven by *Engineering/Heath/Teaching/Business* etc.?)
- Reconcile aggregate result with US
  - ⟹ Felten et al. (2019) do find positive association for top income tercile, just not overall
  - ⟹ More professionals in European workforce? Longer time period? Stronger relationship?

2. *Explanation:* test complementarity story directly

$$\Delta_{2011-19}\text{EmploymentShare}_{cso} = \alpha_c + \alpha_s + \beta \cdot \text{AIExposure}_{cso} + \epsilon_{cso}$$

- *Hypothesis:* AI expands employment in occupations where it complements workers

2. *Explanation:* test complementarity story directly

$$\begin{aligned}\Delta_{2011-19}\text{EmploymentShare}_{cso} =& \alpha_c + \alpha_s + \beta_1 \cdot \text{AIExposure}_{cso} + \beta_2 \cdot \text{Complementarity}_o \\ &+ \beta_3 \cdot \text{AIExposure}_{cso} \cdot \text{Complementarity}_o + \epsilon_{cso}\end{aligned}$$

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- Test directly:
  - ⟹ Interact with complementarity measure from Pizzinelli et al. (2023)
  - ⟹ *Professionals* score highly on complementarity = promising

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- Check timing vs. ML take-off
  - $\Rightarrow$ Did the relationship strengthen after 2016?

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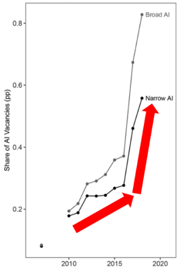
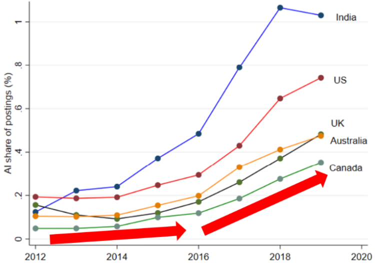
$$\Delta_{2011-19}\text{EmploymentShare}_{cso} = \alpha_c + \alpha_s + \beta \cdot \text{AIExposure}_{cso} + \epsilon_{cso}$$

AI share of vacancies (pp)



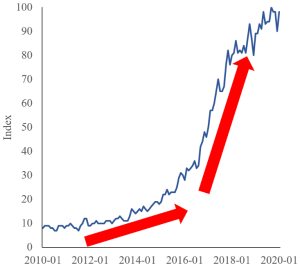
Source: Acemoglu et al. (2022)

AI share of job postings (pp)



Source: Copestake et al. (2023)

Searches for 'machine learning'



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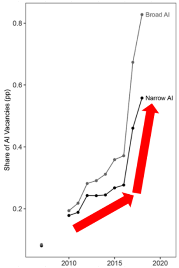

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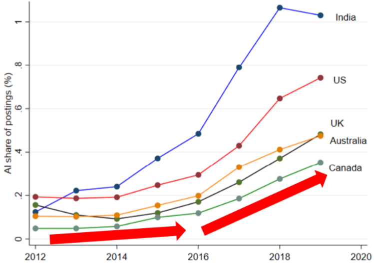

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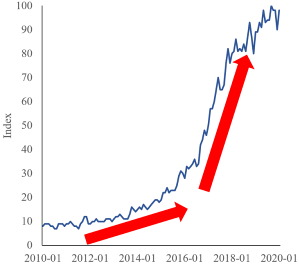

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- Check timing vs. ML take-off

  $\Longrightarrow$ Did the relationship strengthen after 2016? Estimate separate βs by end-year

3. *Heterogeneity:* expand cross-country analysis

$$\Delta_{2011-2019}\text{EmploymentShare}_{cso} = \alpha_c + \alpha_s + \sum_j \left(\beta_j \cdot \text{AIExposure}_{cso} \cdot \mathbb{1}_{\{c=j\}} \right) + \epsilon_{cso}$$

$$Corr_{\text{Spearman}} = \frac{Cov\left[\text{rank}(\beta_c), \text{rank}(Z_c)\right]}{\sigma_{\text{rank}(\beta_c)} \cdot \sigma_{\text{rank}(Z_c)}}$$

- Two steps: estimate country-wise β_cs, then correlate with characteristic Z_c (e.g., PMRs)

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- Two steps: estimate country-wise β_cs, then correlate with characteristic Z_c (e.g., PMRs)
- One-step procedure would be easier to interpret
  - $\Rightarrow$ Include all Z_cs directly in one regression, get one β for each Z_c
  - $\Rightarrow$ Partial correlations, comparable magnitudes, inference, + uses all variation (beyond ranks)

$$\Delta_{2011-2019}\text{EmploymentShare}_{cso} = \alpha_c + \alpha_s + \boldsymbol{\beta}^T \left(\boldsymbol{Z}_c \cdot \text{AIExposure}_{cso} \right) + \epsilon_{cso}$$

Conclusion

- Very interesting paper! Important topic, new cross-country perspective, carefully executed
- Suggested potential extensions:
  1. Unpacking role of professionals
  2. Testing complementarity explanation
  3. Expanding analysis of heterogeneity across countries

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