

The New Wave? The Role of Human Capital and STEM Skills in Technology Adoption in the UK

By Draca, Nathan, Nguyen-Tien, Oliveira-Cunha, Rosso, and Valero

Discussion by Alex Xi He
University of Maryland

WEFI
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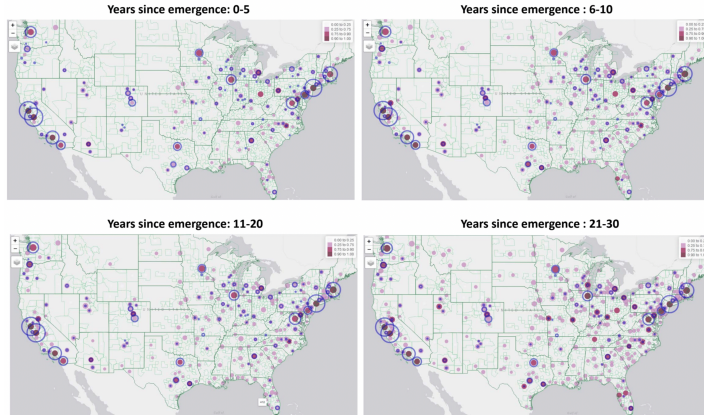
Summary

- **Broad question:** How does human capital affect technology adoption?
- **This paper:** compare two waves of new technologies: personal computer and AI. It also looks at general skills vs. STEM skills.
- It finds that general skills are important for both waves, but STEM skills become much more important in predicting AI adoption.

Context 1: Determinants of technology adoption and diffusion

- Technology diffusion is often slow and uneven (Kalyani et al., QJE forthcoming)

Figure 5 – Geographic diffusion of technology job postings, by year since emergence



- Some technological transitions are faster than others (Adão et al., 2024)

Context 2: Skill-biased technological change

- A major determinant of technology adoption is relative input cost and input supply
Acemoglu and Finkelstein (2008), Hornbeck and Naidu (2014), Hanlon (2015), Hornbeck et al., (2024)
- Technology is biased toward high-skilled labor if it increases the relative demand of high-skilled labor
- Directed technical change (Acemoglu, 2002): an increase in high-skilled labor increases the the value of technologies that are complementary to high-skilled labor
- Technology is not always skill-based: in the late 18th century, migration of unskilled workers to English cities led firms to adopt technologies which favor unskilled workers (factories replace artisan shops)

Very Interesting Paper

- This paper looks at the latest general purpose technology—AI, and contrasts with a previous GPT: personal computers
- The skill bias of AI technologies is not well understood
 - May have similar skill bias as IT
 - But could be different: AI can replace high-skilled college-educated labor, and empower less skilled workers (Webb, 2019)
 - The paper also proposes a new bias: STEM-biased technology adoption
- Important implications for productivity and inequality

Comment #1: Is the comparison fair?

- The main specification for PC is:

$$PC_{j,2000-2002} = \gamma_1 \ln\left(\frac{S}{U}\right)_{j,1991} + \Pi Z_{j,1991} + \epsilon_j$$

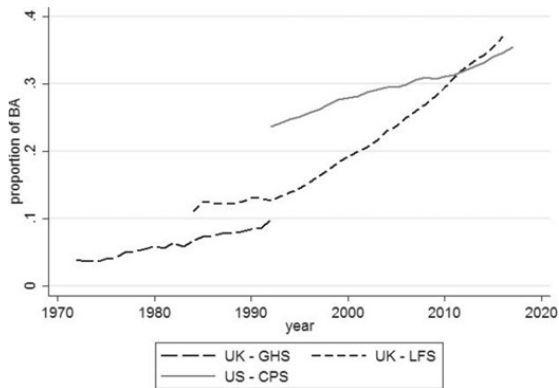
- The main specification for AI is:

$$AI_{j,2019} = \gamma_1 \ln\left(\frac{S}{U}\right)_{j,2011} + \Pi Z_{j,2011} + \epsilon_j$$

- There are two differences across the two specifications:
 - Difference in time period
 - Difference in the life cycle of the technology

Difference in time period

- The share of college graduates grew from about 10% in 1991 to over 30% in 2011 (Blundell et al., 2022)



- The average quality of college graduates may be diluted (Carneiro and Lee, 2011)

Difference in time period

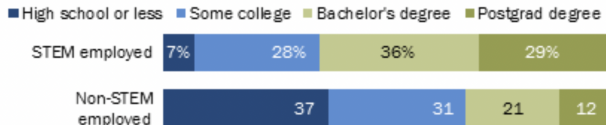
- Babina et al. (2023): while college-degree workers do not predict AI adoption, workers with post-graduate degrees do

	Δ Share of AI Workers 2010-2018			
	(1)	(2)	(3)	(4)
Share of Workers with Low Seniority, 2010	-0.211 (0.393)			-0.394 (0.414)
Share of Workers with Medium Seniority, 2010	-0.443 (0.407)			-0.152 (0.425)
Share of Workers with College Degree, 2010		-0.489** (0.232)		-0.457* (0.245)
Share of Workers with Master Degree, 2010		0.891** (0.402)		0.590* (0.310)
Share of Workers with Doctor Degree, 2010		1.766** (0.819)		2.933*** (0.906)
Share of Workers with STEM Major, 2010			0.741** (0.326)	1.238*** (0.447)
Share of Workers with Social Science Major, 2010			-0.219 (0.286)	0.563** (0.232)
Share of Workers with Fine Arts Major, 2010			0.185 (0.661)	1.021 (0.734)
Share of Workers with Humanities Major, 2010			1.321* (0.694)	0.979 (0.675)

- Suggestion: add the share of post-graduate degrees in the specification

About three-in-ten STEM workers have a postgraduate degree

Educational attainment of employed adults ages 25 and older (%)



Note: Figures may not add to 100% due to rounding. Some college includes those with an associate degree and those who attended college but did not obtain a degree. Postgrad degree includes those who have completed a master's, professional or doctoral degree. STEM stands for science, technology, engineering and math.

Source: Pew Research Center analysis of 2014-2016 American Community Survey (IPUMS). "Women and Men in STEM Often at Odds Over Workplace Equity"

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Difference in life cycle of the technology

- Personal computer started in 1980s and already matured in 2001/2002 (the average number of PCs per employee is 0.72!)
- However, AI technology is still in early stages in 2019 (>70% of firms have zero AI jobs)
- The skill bias of technologies evolve over time (Kalyani et al., QJE forthcoming)
 - In particular, the mean required skill level of the jobs associated with new technologies tends to decline over time, referred to as “skill broadening”
- Suggestion: look at the dynamics of skill bias as technology matures over time, especially for PC

Comment #2: Endogeneity

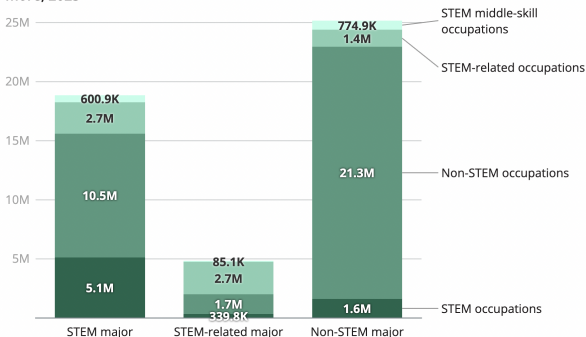
- For the main message (AI technologies are unevenly distributed and exacerbate regional inequality), you only need raw correlations
- But the paper tries to control for “confounders” (e.g., industry structure) to address omitted variable bias
 - Not sure if this is needed: industry differences reflect endogenous technological choice across different industries in response to skill composition
 - Would be useful to show specifications without these controls
- When is the causal estimate of the effect of skill supply on technology adoption useful?
 - To test theories of directed technical change
 - To predict the impact of policies targetting the supply of skilled labor (e.g., immigration)
- Then, the ideal experiment is to compare two regions/firms that are identical except having different skill composition prior to technology adoption
 - Would need a shock to the supply of skilled labor: immigration, opening/expansion of universities

Comment #3: Measurement of STEM skills

- The paper measures STEM skills using the share of workers in STEM occupations at the region level (UK Census) and firm level (Lightcast job postings)
- But it can create several issues:
 - People with STEM skills may not work in STEM occupations (expecially when labor reallocate across sectors during technological transitions)

Most STEM majors work in jobs not classified as STEM

Full-time (35+ hours/week), year-round (50+ weeks) workers with a bachelor's degree or more, 2023



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 - For PC, the share is measured in 1991, which responded endogenously to earlier PC adoption in the 1980s
 - At the firm level, the demand for STEM skills can deviate from the stock of STEM skills among existing workers (firms can reallocate their existing workers with STEM skills instead of hiring new ones)
- Suggestions:
 - Cross-validate with aggregate data on STEM skills (UK version of ACS?)
 - Look at shocks to the supply of STEM skills

STEM-biased technology adoption

- The notion of STEM-biased technology adoption is very interesting
 - Previous literature focus on high-skilled vs low-skilled or man vs machine
- More work is needed to understand the causes and implications
- Babina et al. (2023): AI leads to more product innovation, which increases the demand for STEM workers like engineers
- Deming and Noray (2020): because STEM jobs are fast-evolving, STEM workers get higher earnings when they are young but experience slower wage growth and transition out of STEM jobs when they get older