The New Wave?

Technology Diffusion in the UK during the 2010s

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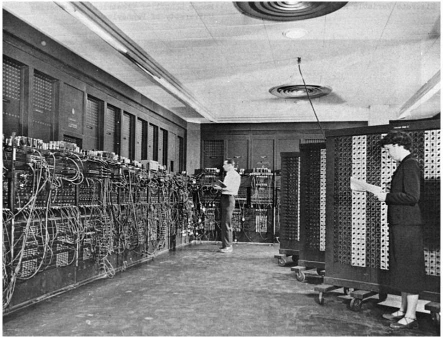
1. Introduction

Computing power through time



ENIAC, the first automatic, general-purpose, electronic digital computer: 30 tons, 18,000 vacuum tubes, **80 bytes**

In 2022, Google Compute Engine VMs scales up to **416 vCPUs** & **11,776 GB** of RAM. Amazon EC2 VMs scales up to **448 vCPUs** & **24,576 GB** of RAMs

1. Introduction

The ICT Revolution enters Middle Age...

- Technological change is widely recognised as a major influence on productivity, growth and patterns of inequality (Acemoglu, 1998; Bryan and Williams, 2021).
  - Particular relevance of general purpose technologies to diffusion - growth links (Bresnahan *et al.*, 2002; Goldfarb *et al.*, 2022).
  - Particular relevance of these questions now, given productivity puzzle.

- Many previous studies look at ICT. But ICT is no longer new, the PC revolution started in the early 1980s, the web took off in the 1990s. These are approaching-middle-age technologies.

- The ICT revolution therefore needs to be considered in terms of different stages or 'waves'.

1. Introduction

Informing the 'second wave' of the ICT revolution...

- A new wave of GPTs (incl. cloud and ML/AI) has emerged in the last decade. Tech optimists expect improved productivity growth once the new wave diffuses widely across the economy (Brynjolfsson *et al.*, 2021), others are more sceptical.

- Understanding patterns and drivers of diffusion to date is therefore key for informing growth policy.

- Research Questions
    - What is the distribution of key 'new wave' technologies across firms and regions?
    - What explains this?
        - Firm vs sector vs area characteristics (esp. skills)
        - Path dependence/overlapping tech waves
        - Differences between our two GPTs
    - *To do later: what is the impact of the new wave on (spatial) wage inequality?*

1. Introduction

What We Do

- Compare patterns of endogenous technological adoption across two major waves of ICT: the PC revolution and the modern 'big data' wave (in particular, cloud and ML/AI technologies, both of which have some GPT characteristics, and which are of course related).

- Main focus is the nature of skill-biased adoption, in particular exploring complementarities between 'general' and 'specific' (technical/STEM) human capital and adoption of digital technologies.

- Underpinned by a comprehensive new approach for measuring technology adoption in firms using job vacancy text. First of its type for the UK.

1. Introduction

What We Do - More practically

- An area level analysis at the Travel to Work Area (TTWA) level (N = 170). Compare the skill bias of adoption for the PC wave versus the 'big data' wave.
- A firm-level analysis for the 2010s where we can measure firm-specific skills. Distinguish between different elements of the 'big data' wave (eg: cloud versus AI).
- Nest this within a 'neo-classical technology adoption' framework as per Beaudry *et al.* (2010). Main innovation is to add two levels of skilled workers and two 'revolutions' or waves.

1. Introduction

Main Findings

- All studied technologies are ‘skilled-biased’ in the sense that they are adopted more intensively where skilled workers are relatively abundant.
- For second wave, comparative advantage in technical skills (STEM) become much more important in attracting the adoption of new technologies than general skills.
- There is a distinctive pattern in the growth of extensive vs intensive margin of technology adoption in the second wave. Over time, more firms of all types engage in new technologies but the adoption rate accelerates aggressively within top STEM-intensive firms, widening the gap.

1.Introduction

Related Literature

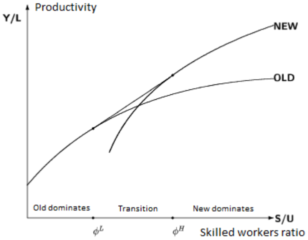
- Historical technology diffusion (David, 1990, Perez, 2010).
- Spatial diffusion, path-dependence and location jumps (Brezis and Krugman, 1997, Duranton, 2007, Berkes et al., 2021).
- Micro frameworks explaining these patterns:
    - **Information asymmetries and localised learning** (Geroski, 2000)
    - **Differences in adoption cost/benefits** (Stoneman and Battisti, 2010)
    - **Complementarities** at firm and/or area level (Nelson and Phelps, 1966, Bresnahan et al., 2002, Beaudry et al., 2010, Balland et al., 2020, Feng and Valero, 2020)
- Tracking diffusion of technologies and impacts on labour markets using job ads (e.g. Bloom et al., 2021; Goldfarb et al., 2022; Webb, 2020)

2. Theoretical Framework

2. Theoretical Framework

- Our analyses are based on skill-biased technological change model by Beaudry *et al.* (2010) that explains the diffusion pattern of PC in the US between 1980-2000 as a 'technological revolution'.
- This paper also considers educational attainment and the return to skills. At this stage we focus on technological diffusion.
- The main idea is that a new technology does not diffuse randomly across space but follows comparative advantages. It is aggressively adopted where the complementary factors are relatively abundant (and cheap).

2. Theoretical Framework



- Price-taking profit-maximising firms decide to adopt old or new technologies to produce goods with a concave, constant- returns-to-scale production function.
- Compared with old technology, the new technology requires new form of capital (PC) and uses skilled labours more intensively (higher S/U ratio).
- For certain rental rates of capitals, the old technology is more productive when used with a small fraction of skilled workers. Otherwise the new technology is more productive.
- Beaudry *et al.* (2010) predict that when a skill-biased technology arrives, the adoption rate will be an increasing function of a locality's ratio of skilled to unskilled workers.

2. Theoretical Framework

We plan to extend this framework:

- For PC in the UK in early 2000s (first wave).
- For Cloud Computing and Machine Learning / Artificial Intelligence (ML/AI) in the UK in 2010s (second wave).
- Propose to include specific technical human capital as another factor that complements new technologies. We later empirically proxy this by the share of 'STEM' workers, which are considered closely linked to high technologies (Hecker, 2005; NESTA, 2015).

3. Data

3. Data

First Wave - Personal Computer

We measure PC adoption using data provided by Harte-Hanks (HH), a multinational company

- The data is designed for the commercial use of large IT firms (e.g., IBM, Cisco, and Dell) (Bloom *et al.*, 2015).
- It surveys establishments of large firms (with at least 100 employees across the country) on an annual basis.
- We look at data for the UK in 3 years 2000-02 and map postcodes of establishments to TTWAs using National Statistics Postcode Lookup (NSPL) crosswalk.
- The variables of interest is PC per employee adjusted by size, industry and year fixed effects at the TTWA. ▸ Details

3. Data

Second Wave - ‘Big Data’ Technologies

We use online vacancy data by Burning Glass Technologies (BGT) to track the emergence of new technologies

- Human capital is ‘an input into technology development and diffusion’ and skill requirements reflect ‘firms’ intentions to engage with emerging technologies’ (Goldfarb *et al.*, 2022). See also Tambe and Hitt (2012).

- Technology (AI) adoption can be partially identified through its ‘footprint’ as firm hire workers specialised in that technology (Acemoglu *et al.*, 2020).

- BGT webscrape information across online sources and de-duplicate entries in order to capture the universe of vacancies in a given country as comprehensively as possible.

- We use BGT data for the whole UK from 2012-19, comprising of 59.9 million vacancies in total. Key information (% of non-missing data) includes job description (100%), SOC code (98.3%), county/UA (87.8%), employer name (33.2%), SIC code (32.9%).

3. Data

Other Data

- **Census Data**
  - We collect a range of labour force data from Census 1991 and 2011: resident adult population, skills (share of university graduates), STEM-related workforce (share of Science and Engineering professionals and associate professionals).
  - We aggregate data from output-area level (OA) or local authority districts (LAD) to TTWA level (2011).
  - STEM worker data is only available for England and Wales (N=170). We use this as our baseline sample for all TTWA-level regressions.[1]
- **Broadband data**: Broadband average speed (2011) at LAD level from Ofcom Communications Infrastructure Reports, aggregated to TTWA level.

[1] The UK is currently divided into 228 TTWAs based on 2011 Census data: 149 in England, 45 in Scotland, 18 in Wales, 10 in Northern Ireland, and 6 cross-border TTWAs. For consistency with BGT, we merge two contiguous pairs: 'London' with 'Slough and Heathrow' and 'Bournemouth' with 'Poole'. Our baseline regressions exclude Boston as it has unusually high PCs per employee. Our results are robust to this exclusion.

4. Methods

4. Methods

Tracking New Technologies

Bloom *et al.* (2021) propose a method that uses expert-curated keyword to track the diffusion of 'Disruptive Technologies':

- intersect USPTO 'hard technology' information (1976-2016) with company earnings call text (2002-2020) to detect 305 bigrams that are both scientifically and economically important.
- use 'supervised' machine learning to group these bigrams into 29 technologies.
- claim that these technologies reflect recent advances in innovation that largely impact businesses and employment within the last two decades.

4. Methods

Tracking New Technologies (cont.)

We adapt this method for the UK context

- implicitly assume a similar pattern in business and technological activities as the US.
- standardise BGT job advert text (e.g: lowercase, remove special characters).
- feed bigrams built in Bloom *et al.* (2021) into preprocessed text. For each of 29 technologies, we flag a job advert exposed to that technology (assign 1) if its text contains any associated bigrams; otherwise zero.
- inspect vacancy posts with unusual 4-digit SIC or 4-digit SOC code (eg: cloud computing expertise amongst florists).
- manually review and build a list of common causes for the false positives and set the bigram indicator to zero for related vacancies.
- Compare and validate at sector level with ONS Surveys where applicable.

4. Methods

Tracking New Technologies (cont.)

We aggregate our adoption measure by different dimensions:

- Industrial level: based on SIC codes.
- TTWA level: Originally, BGT provides location information at the city and county/ unitary authority (UA) levels. We use the information on County/UA (less missing data) to map job adverts to TTWAs.
- Firm level: We use "Employer name" and 4-digit SIC codes to identify "firms". We focus on a subset of large firms with an average of at least 100 posts per year as the information is more reliable. Among them, we can construct a 'balanced' panel of 1,855 firms for the 2012/19 period.

4. Methods

Regression

- Regress outcomes on baseline measures of skills:

$$Y_{jt} = \gamma_0 + \gamma_1 ln(\frac{S}{U})_{j,t_0} + \varepsilon_{jt} \tag{1}$$

where Y is regression-adjusted 'technology intensity' (per employee or vacancy) in region j at at time t and $(\frac{S}{U})$ is the ratio of skilled to unskilled workers in region j at t_0.

- An extension version includes another proxy for initial supply of STEM workers relative to non-STEM workers

$$Y_{jt} = \gamma_0 + \gamma_1 ln(\frac{S}{U})_{j,t_0} + \gamma_2 ln(\frac{S^{STEM}}{U^{STEM}})_{j,t_0} + \varepsilon_{jt} \tag{2}$$

- We also gradually include controls for potential confounding factors such as population density (agglomeration forces), London (unobserved advantages linked to the capital), share of super-fast cables for second wave (digital infrastructure quality).
- All regressions are weighted by working age population.

5. New Technologies Description

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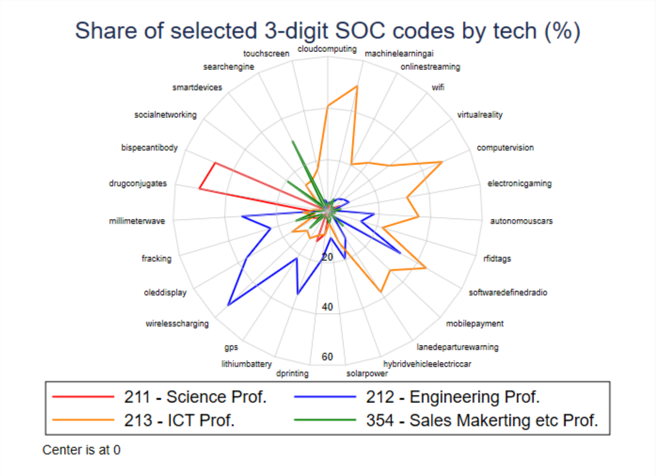
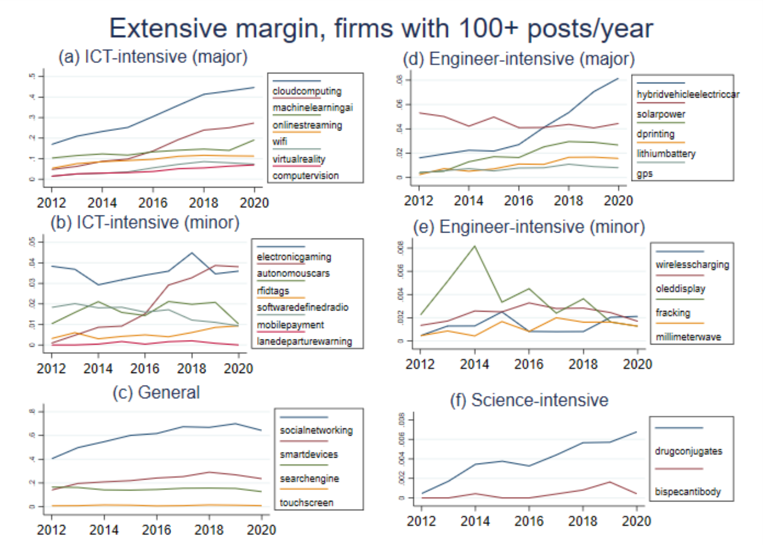
The Role of 21xx SOC codes



- New technologies are characterised by the large hires of STEM occupations, especially science, research, engineering and technology professionals (those with a SOC code starting with 21)
- Digital technologies and ICT professionals are particularly important.

5. New Technologies Description

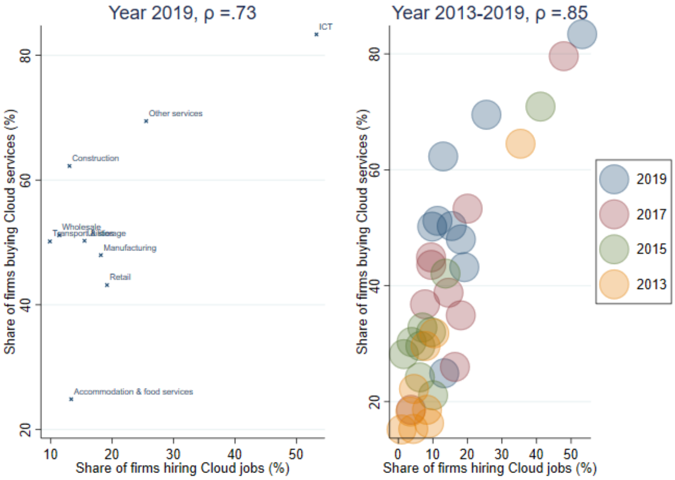
Diffusion Patterns



- The diffusion pattern varies across technologies.
- Some technologies are much more sought after than other in hiring.
- Cloud Computing and ML/AI are the most popular technologies

5. New Technologies Description

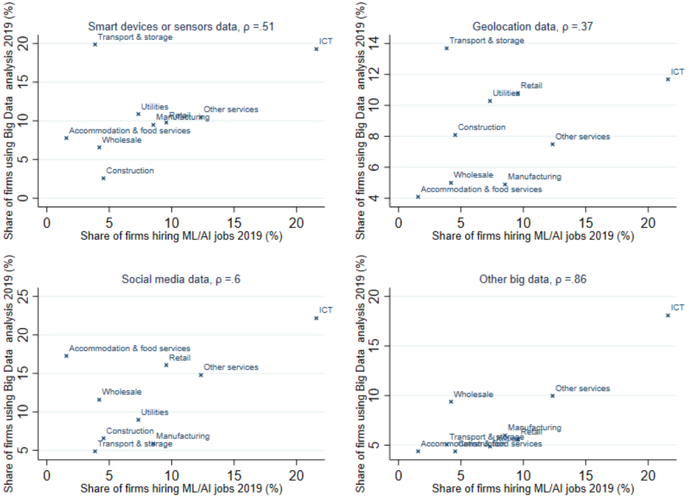
Validation with ONS Surveys



Note: This figure compares the share of firms buying Cloud Services reported in 'E-commerce and ICT activity' annual surveys by ONS and the share of firms hiring Cloud Computing jobs computed from BGT. The comparison include firms have at least 10 employers or post at least 10 online vacancies. We assume firms in BGT can be identified by employer name and SIC code. Correlation coefficients (ρ) are reported for 2019 (Left panel) and 2013/15/17/19 (Right Panel).

5. New Technologies Description

Validation with ONS Surveys



Note: This figure compares the **Share of Firms Using Big Data Analysis 2019** reported in 'E-commerce and ICT activity' annual surveys by ONS and the **Share of Firms Hiring ML/AI Jobs 2019** computed from BGT. The comparison include firms have at least 10 employers or post at least 10 online vacancies. We assume firms in BGT can be identified by employer name and SIC code. Correlation coefficients (ρ) are reported for each type of big data.

6. TTWA Analysis

6. TTWA Analysis

The PC revolution in the UK (1st wave)

Table: First Wave - PC per employee (2000s)

	Weighted	Adjusted	Winsorised & Adjusted		
	(1)	(2)	(3)	(4)	(5)
General skills 1991	0.28***	0.28***	0.17***	0.15***	0.14***
	(0.03)	(0.06)	(0.02)	(0.02)	(0.02)
Pop. density 1991				0.00***	0.00
				(0.00)	(0.00)
London					0.01
					(0.04)
Observations	170	170	170	170	170
R^2	0.391	0.111	0.453	0.487	0.487
Oster test: $\delta_{GeneralSkill1991}$				1.97	0.65

Robust standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

Dependent variable is number of PC per employee. Weighted by employee number. Winsorised top and bottom 1%.

Adjusted by employee number (8 bins), industry (3-digit SIC codes) and year.

6. TTWA Analysis

'Big Data Technologies' (2nd wave)

Table: Second Wave - Adoption rate per 1,000 vacancies

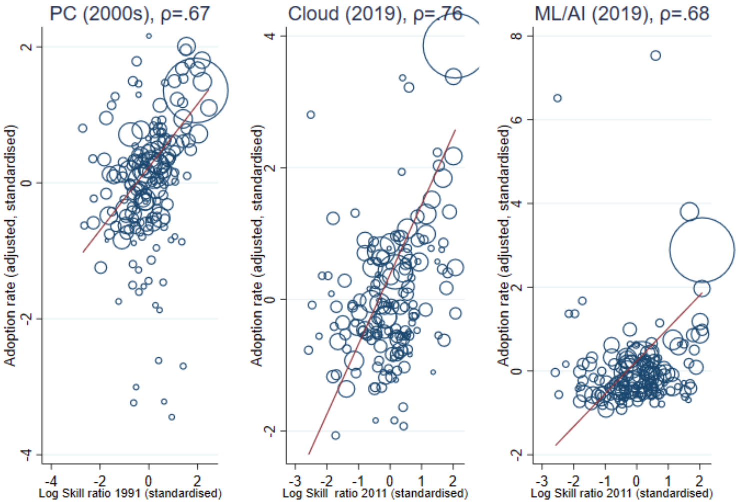
	Cloud Computing 2019			ML/AI 2019		
	(1)	(2)	(3)	(4)	(5)	(6)
General skills 2011	14.49***	8.94***	6.96***	5.22***	3.28***	2.02***
	(3.88)	(1.13)	(1.38)	(1.53)	(0.67)	(0.73)
Pop. density 2011		0.36***	0.14**		0.13***	-0.02
		(0.04)	(0.06)		(0.02)	(0.03)
London			6.57***			4.18***
			(1.71)			(0.65)
Observations	170	170	170	170	170	170
R^2	0.573	0.785	0.807	0.466	0.627	0.684
Oster test: $\delta_{GeneralSkill2011}$		2.66	2.11		1.78	1.07

Robust standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Depdent variables are Adoption rate per 1,000 vacancies, adjusted for firm size (8 bins), industry (3-digit SIC codes) and year FE.

6. TTWA Analysis

Two Waves and General Skills



Note: Dependent variables are number of PC per employee (2000-02) and share of vacancies exposed to cloud computing and ML/AI. All dependent variables are regression-adjusted (for establishment size and industry) and standardised.The graph titles report correlation coefficient ρ.

6. TTWA Analysis

Two Waves and General Skills

Table: Adoption Rate (standardised)

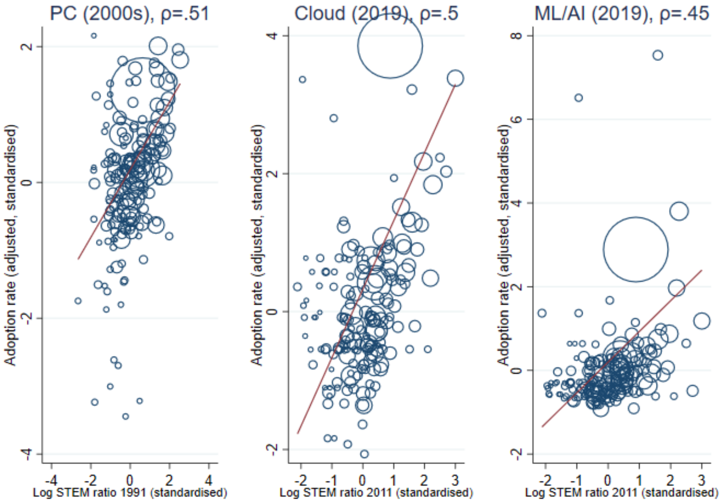
	(1) PC (2000s)	(2) Cloud (2019)	(3) ML/AI (2019)
Baseline General Skills (std.)	0.40***	0.51***	0.30***
	(0.06)	(0.10)	(0.11)
Baseline Population Density (std.)	0.06	0.14**	-0.03
	(0.04)	(0.06)	(0.05)
London	0.08	1.83***	2.39***
	(0.27)	(0.48)	(0.37)
Observations	170	170	170
R^2	0.487	0.807	0.684

Robust standard errors in parentheses.* p$<$0.1, ** p $<$0.05, *** p$<$0.01.

Baseline = 1991 for PC and 2011 for Cloud and ML/AI

6. TTWA Analysis

Two Waves and STEM Skills



Note: Dependent variables are number of PC per employee (2000-02) and share of vacancies exposed to cloud computing and ML/AI. All dependent variables are regression-adjusted (for establishment size and industry) and standardised.The graph titles report correlation coefficient ρ.

6. TTWA Analysis)

Two Waves and STEM Skills

Robustness checks

Table: Adoption Rate (standardised)

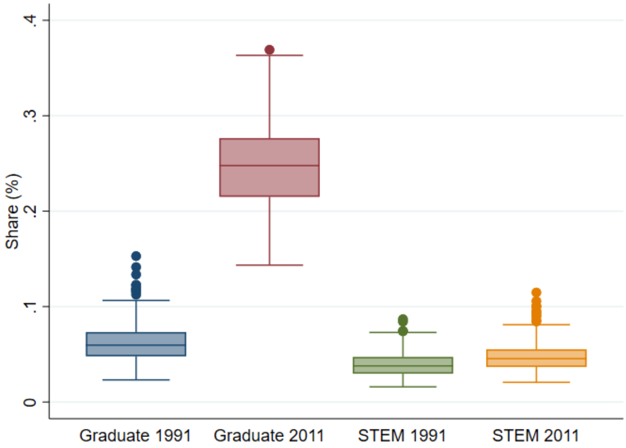
	(1) PC (2000s)	(2) Cloud (2019)	(3) ML/AI (2019)
Baseline General Skills (std.)	0.23***	0.15	-0.03
	(0.08)	(0.10)	(0.10)
Baseline STEM Skills (std.)	0.27***	0.51***	0.48***
	(0.08)	(0.12)	(0.15)
Baseline Population Density (std.)	0.02	0.08	-0.09
	(0.05)	(0.06)	(0.07)
London	0.55	2.66***	3.16***
	(0.35)	(0.45)	(0.50)
Observations	170	170	170
R^2	0.527	0.835	0.719

Robust standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Baseline = 1991 for PC and 2011 for Cloud and ML/AI

6. TTWA Analysis

Graduates become abundant, STEM workers remain rare

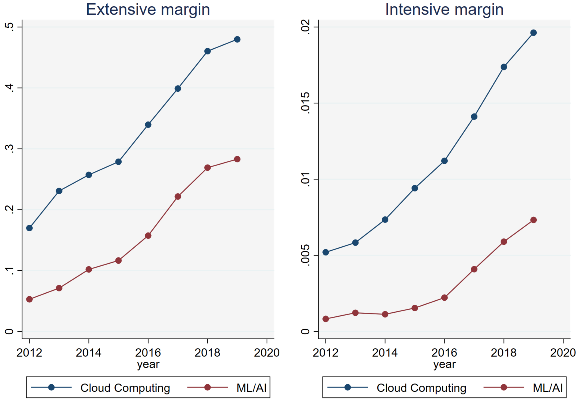


These box plots illustrate the distributions of Graduates shares and STEM shares in 1991/2011 across 170 TTWAs included in the regressions

7. Firm (Balanced) Panel Analysis

7. Firm Panel Analysis

The Rise of New Wave

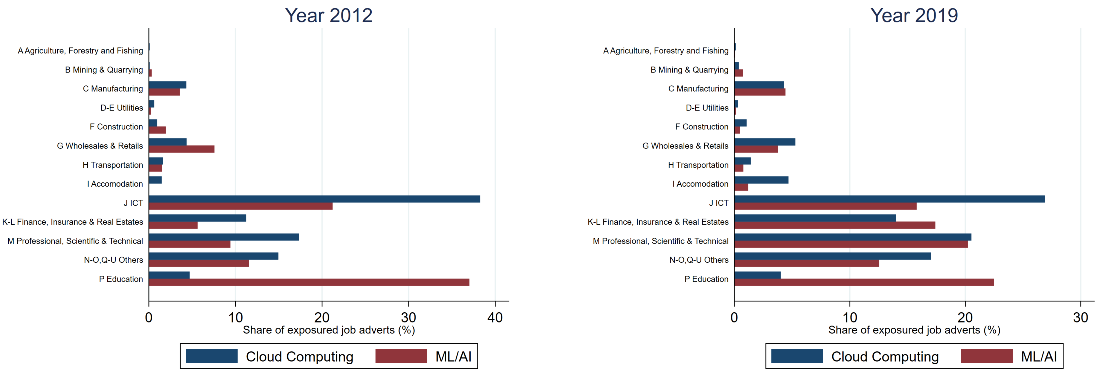


This graph plots the hiring trends of a balanced panel of firms with an average of 100+ posts per year..

- Demand for Cloud Computing and ML/AI grows quickly among large firms with an acceleration between 2015-16 (smilar to the US).
- The trends for two technologies look almost parallel with Cloud Computing being more demanded.

7. Firm Panel Analysis

The Spread of New Wave



These figures depict the industrial composition of all job adverts exposured to Cloud Computing and ML/AI that are assigned a SIC code by BGT.

7. Firm Panel Analysis

Extensive Margin of Adoption is STEM-biased

	Any Cloud Computing Hire?				Any ML/AI Hire?			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% STEM vac. (2012)	1.05***		0.80***	0.71***	0.72***		0.49***	0.56***
	(0.076)		(0.077)	(0.084)	(0.072)		(0.081)	(0.097)
% High skill vac. (2012)		0.52***	0.33***	0.21***		0.38***	0.26***	0.090**
		(0.050)	(0.044)	(0.043)		(0.071)	(0.090)	(0.036)
% Middle skill vac. (2012)		0.058	0.078**	0.035		0.0012	0.014	-0.028
		(0.040)	(0.039)	(0.042)		(0.029)	(0.029)	(0.041)
Year FE	x	x	x	x	x	x	x	x
Size (2012) control				x				x
SIC-2 control				x				x
Observations	16695	16695	16695	16695	16695	16695	16695	16695
ymean				0.34				0.17

Standard errors clustered at 2-digit SIC code level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Skill level is constructed by 1-digit SOC code with the reference group being labour skill level.

7. Firm Panel Analysis

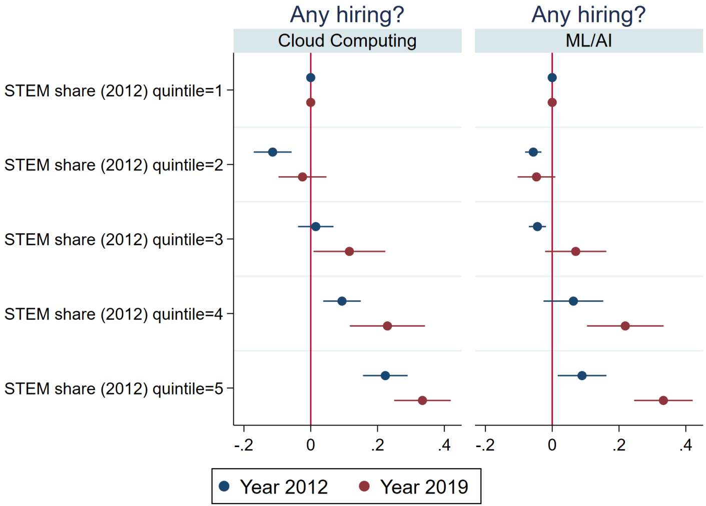
Intensive Margin of Adoption is STEM-biased

	Share of Cloud Computing Hires				Share of ML/AI Hires			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% STEM vac. (2012)	0.09***		0.09***	0.07***	0.02***		0.02***	0.02***
	(0.02)		(0.02)	(0.01)	(0.003)		(0.003)	(0.004)
% High skill vac. (2012)		0.03***	0.01***	0.010***		0.01***	0.006**	0.001
		(0.01)	(0.004)	(0.003)		(0.002)	(0.002)	(0.001)
% Middle skill vac. (2012)		0.005	0.007**	0.003		-0.0004	0.00010	-0.001
		(0.003)	(0.004)	(0.004)		(0.0009)	(0.0009)	(0.001)
Year FE	x	x	x	x	x	x	x	x
Size (2012) control				x				x
SIC-2 control				x				x
Observations	16695	16695	16695	16695	16695	16695	16695	16695
ymean				0.01				0.004

Standard errors clustered at 2-digit SIC code level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Skill level is constructed by 1-digit SOC code with the reference group being labour skill level.

7. Firm Panel Analysis

Extensive Margin of Adoption is STEM-biased

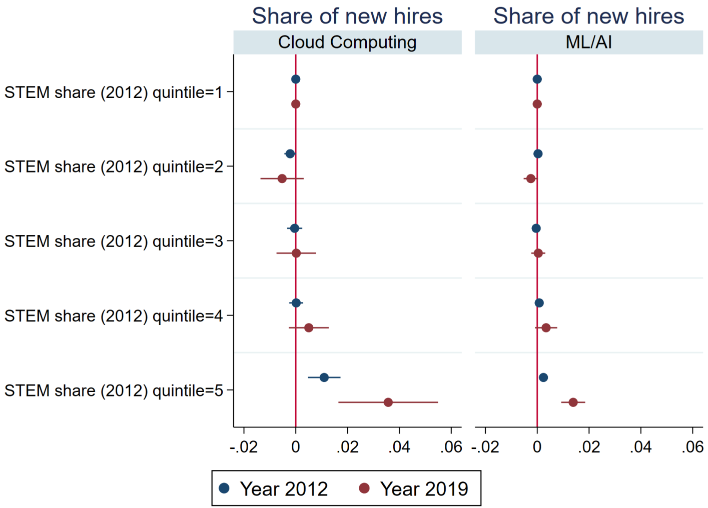


Conditional on other factors (initial firm size, industry, skill contents):

- Firms at higher quintiles are more likely to hire Cloud Computing and ML/AI jobs.
- Hiring decision increases across all quintiles between 2012-19.

7. Firm Panel Analysis

Intensive Margin of Adoption is STEM-biased



Conditional on other factors (initial firm size, industry, skill contents):

- Firms at the top quintile require more Cloud Computing and ML/AI jobs.
- Between 2012-19, demands for these technologies grow extremely fast at the top quintile.

8. Conclusions & Future Work

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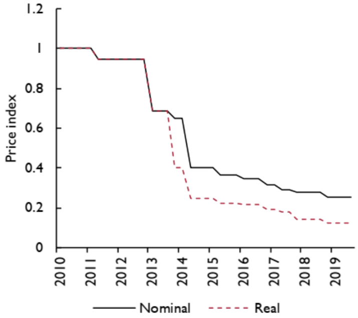
Figure 6. Price index (nominal and quality-adjusted) for AWS General Purpose EC2 xlarge Linux instance, 2010Q1–2019Q3



Source: Coyle and Nguyen (2019)

- We examine the skill-biasedness and STEM-biasedness of new technologies in early 2000s and late 2010s:
  - Skills matter, particularly technical skills, and more so in the second wave
  - At firm level, the most tech-intensive companies appear to be pulling away
- In future work, we plan to validate the prediction of neoclassical model on the increase in return to skills and return to STEM skills where new technologies are intensively adopted.
- Second wave is intrinsically different from first wave as rental rate of capital associated with new technology (cloud price) falls quickly. Studying its implication could be interesting for future work.

Thanks for your attention!

Appendix

Regerssion Adjustment

The variable of interest is number of PCs per employee at the establishment level.

- We map postcodes of establishments to TTWAs using National Statistics Postcode Lookup (NSPL) crosswalk.
- Following Beaudry *et al.* (2010), we calculate TTWA-level PC intensity by regression to remove heterogeneity by establishment size, industry and year fixed effects (after winsorizing the top and bottom 1% outliers)

$$pcpe_{it} = \Phi Ind_i \times Size_i + \Psi Year_t + \Omega TTWA_i + \varepsilon_{it} \tag{3}$$

- $pcpe_{it}$ is (winsorized) number of PCs per employee of establishment i at year t.
- Ind_i, $Size_i$, $Year_t$ and $TTWAi$ are vectors of dummy variables of industry (3 digit SIC), establishment size (in 8 bins), survey year and TTWA where the establishment is located.
- ε_{it} is the idiosyncratic error terms as usual.
- Ω is the vector of coefficients of interest that capture PCs intensity index at the TTWA level after being adjusted for other factors.

▸ Back

Appendix

Falsification test

	Cloud Computing 19		ML/AI 19	
	(1)	(2)	(3)	(4)
Skills 11	2.029		-0.218	
	(1.432)		(0.672)	
Skills 91 (α)		1.383		-0.445
		(1.505)		(0.764)
Skills change 91-11 (α')		-0.835		-1.275
		(2.551)		(1.525)
STEM Skills 11	5.927***		2.691***	
	(1.353)		(0.865)	
STEM Skills 91 (β)		5.693***		2.593***
		(1.367)		(0.812)
STEM Skills change 91-11 (β')		7.169***		2.951**
		(2.450)		(1.480)
London & Density controls	Y	Y	Y	Y
Observations	170	170	170	170
p-value: $\alpha = \alpha'$		0.195		0.416
p-value: $\beta = \beta'$		0.413		0.683

Robust standard errors in parentheses. p $<$0.1, p $<$0.05, p $<$0.01.

Falsification test

- We hypothesise skill supply predicts tech adoption
- What if workers anticipate increase in skill demand driven by new tech? How about other confounders?
- If these happen, we would expect $\alpha \neq \alpha'$ and $\beta \neq \beta'$ as recent changes are more sensitive.

Appendix

Robustness checks: TTWA Analysis

Baseline

Table: Robustness checks -Technology Intensities and Skills

	(1) PC (2000s)	(2) Cloud (2019)	(3) ML/AI (2019)	(4) PC (2000s)	(5) Cloud (2019)	(6) ML/AI (2019)	(7) Cloud (2019)	(8) ML/AI (2019)
Baseline General Skills (std.)				0.15*	0.15	-0.06	0.17	-0.04
				(0.09)	(0.11)	(0.10)	(0.11)	(0.10)
Baseline STEM Skills (std.)	0.45***	0.63***	0.45***	0.37***	0.52***	0.34***	0.36**	0.23*
	(0.07)	(0.09)	(0.13)	(0.09)	(0.12)	(0.11)	(0.15)	(0.13)
Baseline Population Density (std.)	-0.03	0.05	-0.08	0.03	0.08	-0.04	-0.01	-0.12
	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.09)	(0.07)
London	1.19***	3.06***	3.07***	0.48	2.66***	3.10***	2.92***	3.32***
	(0.27)	(0.36)	(0.30)	(0.38)	(0.45)	(0.49)	(0.50)	(0.50)
Oxbridge				-0.27	-0.09	2.42***	-0.02	2.46***
				(0.20)	(0.54)	(0.66)	(0.57)	(0.69)
Share Superfast Broadband							0.64	0.51*
							(0.50)	(0.29)
PC per Employees (adj win std)							0.11	0.05
							(0.09)	(0.06)
Observations	170	170	170	170	170	170	170	170
R^2	0.494	0.832	0.719	0.529	0.835	0.781	0.839	0.784

Robust standard errors in parentheses. p <0.1, p <0.05, p <0.01.

Baseline = 1991 for PC and 2011 for Cloud and ML/AI

Appendix

Robustness checks: TTWA Analysis

Baseline

Table: Robustness checks with Unadjusted Variables

	(1) PC (2000s)	(2) Cloud (2019)	(3) ML/AI (2019)	(4) PC (2000s)	(5) Cloud (2019)	(6) ML/AI (2019)	(7) Cloud (2019)	(8) ML/AI (2019)
Baseline General Skills (std.)	0.33***	0.24**	0.10	0.34***	0.24**	0.07	0.26**	0.11
	(0.08)	(0.10)	(0.10)	(0.08)	(0.10)	(0.09)	(0.10)	(0.09)
Baseline STEM Skills (std.)	0.04	0.62***	0.49***	0.04	0.63***	0.36***	0.48**	0.29**
	(0.08)	(0.16)	(0.14)	(0.09)	(0.17)	(0.11)	(0.21)	(0.13)
Baseline Population Density (std.)	0.04	0.25***	0.05	0.04	0.25***	0.09	0.15	0.03
	(0.06)	(0.08)	(0.07)	(0.06)	(0.08)	(0.06)	(0.10)	(0.07)
London	0.12	1.72***	2.86***	0.12	1.73***	2.80***	2.01***	3.04***
	(0.41)	(0.63)	(0.46)	(0.41)	(0.63)	(0.44)	(0.68)	(0.47)
Oxbridge				-0.07	-0.11	2.40***	-0.05	2.41***
				(0.20)	(0.37)	(0.51)	(0.39)	(0.53)
Share Superfast Broadband							0.65	0.46*
							(0.44)	(0.28)
PC per Employees (adj win std)							0.08	-0.03
							(0.08)	(0.05)
Observations	170	170	170	170	170	170	170	170
R^2	0.413	0.866	0.818	0.413	0.866	0.860	0.869	0.862

Robust standard errors in parentheses. p <0.1, p <0.05, p <0.01.

Baseline = 1991 for PC and 2011 for Cloud and ML/AI

Appendix

Robustness checks: TTWA Analysis

Baseline

Table: Robustness checks - No weights

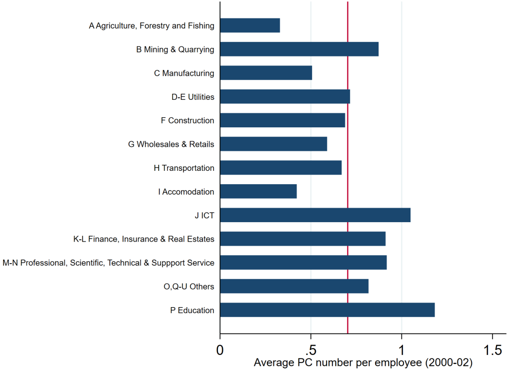
	(1) PC (2000s)	(2) Cloud (2019)	(3) ML/AI (2019)	(4) PC (2000s)	(5) Cloud (2019)	(6) ML/AI (2019)
Baseline General Skills (std.)	0.10	0.14	-0.15	0.09	0.13	-0.17
	(0.09)	(0.11)	(0.15)	(0.09)	(0.11)	(0.15)
Baseline STEM Skills (std.)	0.32***	0.28**	0.35***	0.32***	0.27**	0.29**
	(0.10)	(0.12)	(0.13)	(0.10)	(0.12)	(0.13)
Baseline Population Density (std.)	0.09	-0.01	-0.14	0.09	-0.00	-0.11
	(0.06)	(0.08)	(0.11)	(0.06)	(0.08)	(0.10)
London	0.47	3.39***	3.78***	0.48	3.39***	3.76***
	(0.37)	(0.60)	(0.81)	(0.38)	(0.61)	(0.81)
Oxbridge				0.18	0.34	2.57***
				(0.22)	(0.56)	(0.69)
Observations	170	170	170	170	170	170
R^2	0.173	0.219	0.131	0.174	0.220	0.202

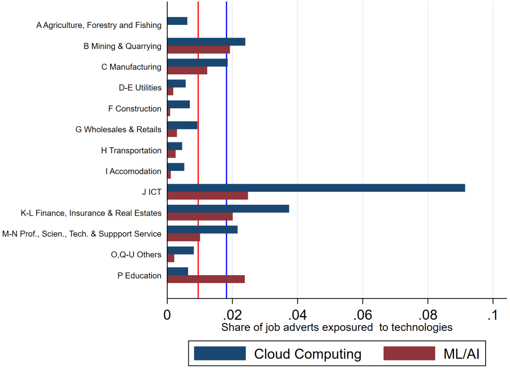
Robust standard errors in parentheses. p $<$0.1, p $<$0.05, p $<$0.01.

Baseline = 1991 for PC and 2011 for Cloud and ML/AI

Appendix

Adoption by Industry





These figures depict the industrial composition of all job adverts exposured to Clould Computing and ML/AI posted by large firms (100+ posts/year on average)

Appendix

Firm Sub-sample Regression

Table: **Extensive Margin - Subsample Regressions**

	Any Cloud Computing Hire?		Any ML/AI Hire?	
	(1) 2012	(2) 2019	(3) 2012	(4) 2019
firstsharestem	0.53***	0.67***	0.25**	0.79***
	(0.090)	(0.11)	(0.098)	(0.13)
firstsharehighskill	0.21***	0.23**	-0.0094	0.26***
	(0.038)	(0.095)	(0.025)	(0.066)
firstsharemiddleskill	0.11***	-0.016	-0.048	0.034
	(0.036)	(0.10)	(0.035)	(0.065)
Size (2012) control	x	x	x	x
SIC-2 control	x	x	x	x
N	1855	1855	1855	1855
ymean	0.17	0.48	0.053	0.28

Standard errors clustered at 2-digit SIC code level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Appendix

Firm Sub-sample Regression

Table: **Intensive Margin - Subsample Regressions**

	Share of Cloud Computing Hires		Share of ML/AI Hires	
	(1)	(2)	(3)	(4)
	2012	2019	2012	2019
firstsharestem	0.033***	0.091***	0.0083**	0.042***
	(0.011)	(0.014)	(0.0035)	(0.0073)
firstsharehighskill	0.0031*	0.011	-0.0011	0.0034
	(0.0016)	(0.0071)	(0.00063)	(0.0029)
firstsharemiddleskill	0.0011	0.0058	-0.0012	-0.0011
	(0.0017)	(0.010)	(0.00077)	(0.0023)
Size (2012) control	x	x	x	x
SIC-2 control	x	x	x	x
N	1855	1855	1855	1855
ymean	0.0052	0.020	0.00082	0.0073

Standard errors clustered at 2-digit SIC code level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

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