More than Just Plug & Play:
Early Evidence on AI and Organizational Capital

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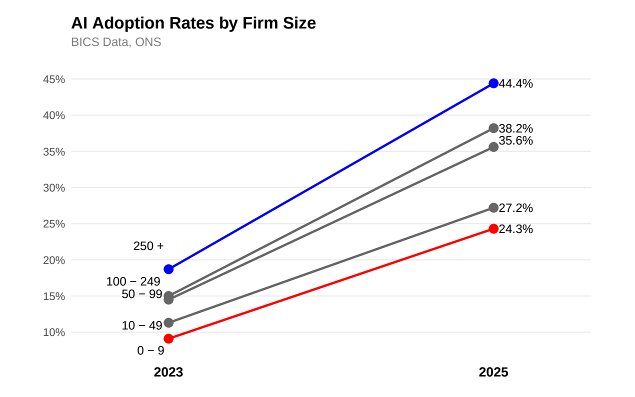
Why is the speed of adoption uneven?

- AI promises substantial productivity gains for firms.[a]
- Early evidence of productivity gains.[b]
- Costs are falling rapidly, making adoption increasingly feasible for most users. cost
- **But some firms adopt much faster than others**



Source: Authors' calculation; Business Insights and Conditions Survey (BICS)

[a] See McKinsey & Company 2023

[b] See Siedschlag and Duran Vanegas 2025; Silva Marioni, Rincon-Aznar, and Venturini 2024

We need to understand what drives this two speed-adoption

1. **Productivity implications**
   - AI concentrated among large firms → widening productivity gap
   - Small firms falling behind → economy-wide productivity drag
2. **Policy design**
   - Are financial barriers the constraint?
   - Or organizational capabilities?
   - Determines optimal intervention strategy
3. **Theoretical insight**
   - What makes some technologies harder to adopt?
   - Role of organizational capital in technology diffusion

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What we do...

- Using a unique dataset developed by ESCoE and the ONS, we examine the relationship between AI Adoption and "better management practices".
- We compare organizational capital requirements of AI with other technologies.
- We explore possible mechanisms as to why.

Spoilers

- AI is more associated with organizational capital for adoption compared to other technologies
- Firms that are good at setting targets are more likely to adopt AI
- AI adoption is higher with decentralized product development

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What we know about technology adoption

The Economics Literature

- **Intangibles as complements** technology adoption
- Brynjolfsson and Lorin M. Hitt 2000 Bresnahan, Brynjolfsson, and Lorin M Hitt 2002
- **J-Curve:** Brynjolfsson, Rock, and Syverson 2021
- **Management practices:** Bloom, Sadun, and Reenen 2012

Literature on Organizational Studies

- The Diffusion of Innovations (DOI) theory: innovation characteristics, adopter characteristics, and communication channels (Rogers 2003).
- The Technology-Organisation-Environment (TOE) framework: technological, organisational and environmental context (Tornatzky, Fleischer, and Chakrabarti 1990).

What does past research say?

Technological factors	Technological infrastructure and resources
	R&D
	Employee expertise
External	External pressure
	Business and vendor partnership
Organisational factors	Firm size
	Top management support
	Management practices and quality
	Decentralisation

We use new data from the ONS

UK Management and Expectations Survey (MES)

- Conducted every three years (2017, 2020 and 2023)
- The 2023 MES sampled over 53,000 firms and achieved a response rate of 26.9%
- Excluding micro-businesses (fewer than 10 employees) and those in agriculture, financial services and the public sector.
- Bloom and Van Reenen 2007

How we measure management practices

- Based on 23 questions on management approach.
- Comparable to the US's Management and Organizational Practices Survey (MOPS)
- Summarize management quality to a "Management Score"
- Correlates with Turnovers, Employment, Profitability. (Awano et al. 2018; Bloom and Van Reenen 2007; Vyas 2018)

Four components:

- Continuous improvement: How well does the company resolve problems and use that information to improve?
- Key performance indicators (KPIs): How many KPIs and how often are they reviewed?
- Targets: Timeframes, feasibility and awareness of targets; target-based incentives.
- Employment practices: Pratices relating to promotion, training and employee underperformance.

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Technology adoption

- First asked in 2023 wave (we do not have a full panel).
- AI, Cloud computing, Robotics, Specialized Software, Specialized Equipment.
- They define the technology for users.
- Not all respondents answered these questions.

We construct...

A binary indicator of technology adoption in 2023

$= \mathbf{1}$ if "Used as part of processes or methods"

$= \mathbf{0}$ if "Applicable, but have not tested or used"

Note: We tried other variations of the dependent variable but this specification ensures that we account for technological relevance.

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Only a few firms adopt AI in our sample

	AI	Cloud Computing	Robotics	S. Software	S. Equipment
Not applicable to business	50.0%	8.4%	64.9%	13.6%	32.2%
Applicable, not tested/used	18.5%	5.9%	12.6%	5.4%	6.0%
Tested but not used	9.2%	5.3%	2.5%	4.4%	3.7%
Used in processes/methods	8.6%	75.1%	8.5%	70.0%	47.4%
Don't know	13.6%	5.3%	11.4%	6.7%	10.7%
Total respondents	100%	100%	100%	100%	100%

Notes: Share of respondents (N=7,525) in merged 2020-2023 MES sample. Excludes non-respondents.

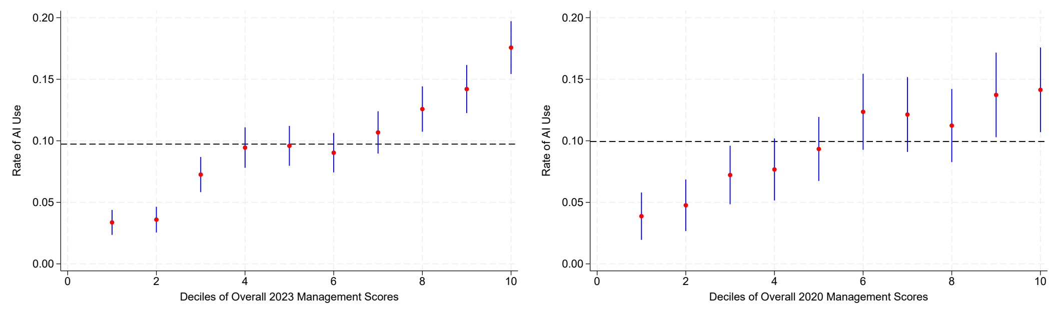
Distribution by industry is substantially different

	AI	Cloud Computing	Robotics	S. Software	S. Equipment
Non-Manuf. Production	1.5%	1.9%	s	1.8%	2.6%
Manufacturing	14.6%	19.1%	56.2%	20.4%	32.7%
Construction	4.2%	6.6%	2.8%	6.4%	7.4%
Distribution, hotels	22.0%	21.0%	17.3%	20.8%	22.3%
Transport & Communications	15.5%	8.8%	5.9%	8.9%	7.9%
Business services	26.2%	17.3%	12.8%	16.9%	12.6%
Other services	14.1%	15.0%	4.9%	13.9%	13.6%
Real Estate	1.9%	1.7%	s	1.6%	1.0%
Total respondents	100%	100%	100%	100%	100%

Notes: Share of respondents (N=7,525) in merged 2020-2023 MES sample. Excludes non-respondents.

Adoption rates are higher for firms with higher management scores

Figure 1: AI adoption rate across deciles of management score



2023 2020

Source: Authors' calculations, Office for National Statistics

We use a linear probability model in our baseline regression

$$\Pr(AI = 1)_{i,2023} = \beta_0 + \beta_1 \mathit{Management\ Score}_{i,2020} + \beta_2' X_{i,s,2020} + \beta_3' FE + \varepsilon_{i,1}$$

- Dependent variable: AI adoption in 2023 (binary)
- Key predictor: Management quality score (2020)
- Controls: Log productivity, family management, foreign ownership
- Fixed effects: Size, industry, age, region

We estimate β_1: does better management predict AI adoption?

We also examine...

1. **Technology comparison**: Apply model to cloud computing, robotics, specialized software, and specialized equipment
2. **Management dimensions**: Test effect of each management subcomponent separately
3. **Organizational structure**: Examine role of centralization in AI adoption
4. **Robustness**: Outlier analysis, propensity score matching, non-linear relationship, bigger sample, control for other intangibles.

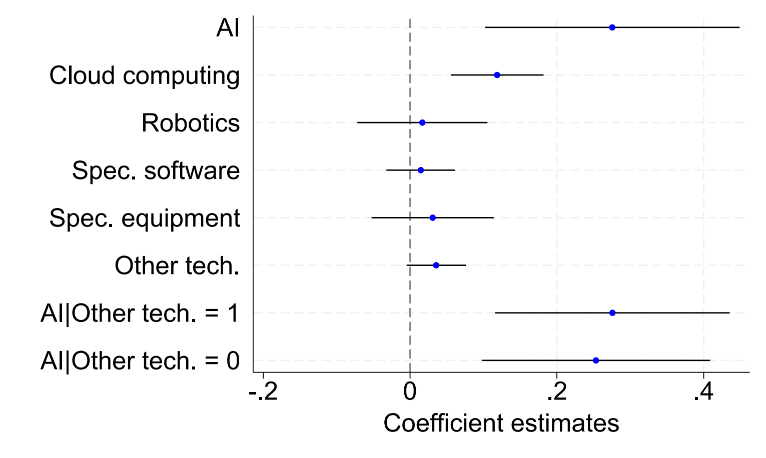
Firms with better management are more likely to adopt AI

	(1)	(2)	(3)	(4)	(5)	(6)
		Pr(AI = 1)			Pr(Plan AI = 1)	
Management Score 2020	0.254**	0.275**	0.279**	0.165**	0.145**	0.151**
	(0.096)	(0.092)	(0.093)	(0.050)	(0.056)	(0.056)
Log Labor Productivity 2020		-0.019	-0.018		0.019	0.022
		(0.015)	(0.016)		(0.016)	(0.018)
Foreign			-0.024			-0.039
			(0.028)			(0.030)
Observations	1292	1292	1292	881	881	881
Adj R2	0.023	0.024	0.024	0.017	0.017	0.017
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations, ONS.

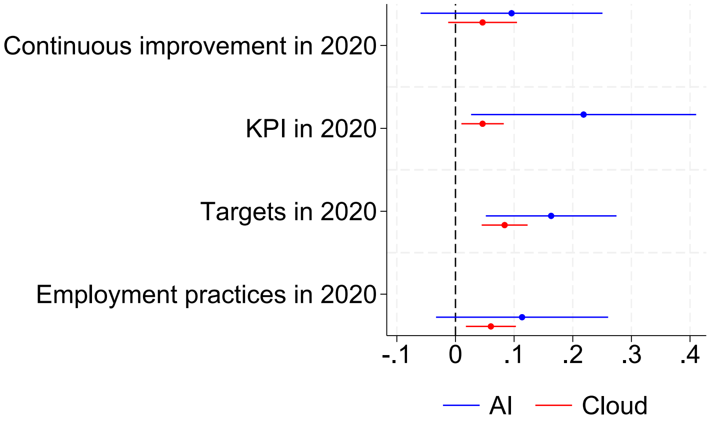
AI versus robots (and other technologies)

Figure 2: Management Practices and Technology Adoption



KPI Tracking and Target Setting are the most relevant

Figure 3: Regression on sub-scores



AI adoption is higher with decentralized product development

	(1)	(2)	(3)	(4)
		Pr(AI = 1)		
Multiple sites	0.045			
	(0.030)			
Centralised recruitment		-0.052		
		(0.040)		
Centralised product development			-0.055**	
			(0.020)	
Centralised investment decision				-0.013
				(0.030)
Management Score 2020	0.271**	0.382***	0.386***	0.416***
	(0.090)	(0.080)	(0.080)	(0.070)
Log Labor Productivity 2020	-0.020	-0.039***	-0.039***	-0.044***
	(0.020)	(0.010)	(0.010)	(0.010)
Observations	1,292	574	574	556
Adj R2	0.026	0.022	0.022	0.028
Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

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Why management matters more for AI

1. **AI requires continuous monitoring and adjustment**
   - Machine learning models degrade as data distributions shifts
   - Unlike robotics: no "set it and forget it"
   - Demands ongoing feedback and refinement
2. **AI outputs need human interpretation**
   - Robots and Specialized Software & Equipment perform specific tasks
   - Creates coordination challenge that structured monitoring addresses

Why Monitoring Capabilities Matter Most

KPI tracking and target-setting predict AI adoption most strongly

But why these specific practices?

Coordination

- Common language for priorities
- Resource allocation decisions
- Track organizational changes

Data Readiness

- Signals digitalization level
- Existing data infrastructure
- AI training/customization ready

Monitoring infrastructure = organizational readiness for AI

AI helps coordination in decentralized adoption

- Easier to find use cases when adoption is coming from the end-user or closer to the product.
- AI applications are highly context-specific $\Rightarrow$ difficult to identify valuable use cases without domain knowledge.

- Decentralized decision rights *without* structured monitoring may lead to fragmented, uncoordinated AI experiments that fail to scale.

Circling Back: Key Takeaways

1. **Productivity implications**
   - Management practices are binding constraint for AI adoption and risks 2-speed growth path
2. **Policy design**
   - Target management practices intervention
   - Support "structured decentralization": autonomy + coordination
   - Different technologies need different policy tools
3. **Theoretical insight**
   - AI requires continuous monitoring and human interpretation
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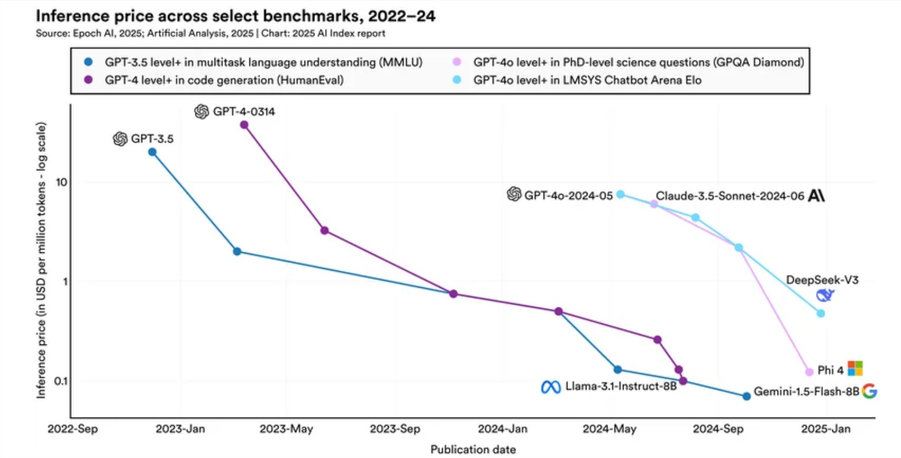
Thank you!

Any feedback or question is welcome!

Appendix

Falling cost of LLMs



back

Summary Statistics

	All	AI Use = 1	AI Use = 0	Diff
Management score 2020	0.600	0.616	0.593	0.023
	(0.163)	(0.157)	(0.165)	
Continuous Improvement 2020	0.870	0.879	0.866	0.013
	(0.187)	(0.175)	(0.192)	
KPI 2020	0.485	0.504	0.476	0.028
	(0.199)	(0.199)	(0.199)	
Targets 2020	0.548	0.566	0.539	0.027
	(0.211)	(0.208)	(0.212)	
Employment Practices 2020	0.665	0.677	0.659	0.018
	(0.225)	(0.224)	(0.225)	
Multiple sites	0.444	0.482	0.427	0.055
	(0.497)	(0.500)	(0.495)	
Centralized recruitment	0.430	0.384	0.455	-0.071
	(0.496)	(0.488)	(0.499)	
Centralized product development	0.605	0.561	0.628	-0.067
	(0.489)	(0.498)	(0.484)	
Centralized investment decision	0.552	0.544	0.556	-0.012
	(0.498)	(0.499)	(0.497)	

	All	AI Use = 1	AI Use = 0	Diff
Labor productivity 2020	217.5	268.8	193.5	75.276
	(1,026.3)	(1,603.1)	(588.2)	
Firm Size (Employment)				
10–19 employees	0.144	0.175	0.129	0.046
	(0.351)	(0.381)	(0.336)	
20–49 employees	0.310	0.280	0.325	−0.045
	(0.463)	(0.449)	(0.469)	
50–99 employees	0.255	0.243	0.260	−0.017
	(0.436)	(0.430)	(0.439)	
100–249 employees	0.168	0.170	0.167	0.003
	(0.374)	(0.376)	(0.373)	
250+ employees	0.123	0.131	0.119	0.012
	(0.329)	(0.338)	(0.324)	

	All	AI Use = 1	AI Use = 0	Diff
Firm Age (Years)				
3–5 years	0.011	0.007	0.012	−0.005
	(0.104)	(0.085)	(0.111)	
6–10 years	0.080	0.090	0.075	0.015
	(0.271)	(0.287)	(0.263)	
11–20 years	0.247	0.290	0.227	0.063
	(0.431)	(0.454)	(0.419)	
20+ years	0.663	0.613	0.686	−0.072
	(0.473)	(0.488)	(0.465)	

Management subcomponents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Pr(AI = 1)				Pr(Plan AI = 1)		
Continuous improvement in 2020	0.096				0.013			
	(1.17)				(0.11)			
KPI in 2020		0.219*				0.092		
		(2.16)				(0.86)		
Targets in 2020			0.165***				0.121	
			(3.50)				(1.85)	
Employment practices in 2020				0.083				0.036
				(1.19)				(0.73)
Log Labor Productivity 2020	-0.014	-0.016	-0.019	-0.015	0.023	0.021	0.017	0.022
	(-0.93)	(-1.02)	(-1.24)	(-0.95)	(1.45)	(1.29)	(1.16)	(1.43)
Observations	1292.000	1292.000	1292.000	1292.000	881.000	881.000	881.000	881.000
Adj R2	0.018	0.025	0.022	0.018	0.015	0.016	0.018	0.015
Fixed Effects			Size, age, industry, and region					

Note: t-stats in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Baseline regression: Other technologies

	(1) Pr(Cloud=1)	(2) Pr(Robotics=1)	(3) Pr(S. Softwr=1)	(4) Pr(Eqpt=1)	(5) Pr(Other tech.=1)	(6) Pr(AI=1)	(7) Pr(AI=1 | Other tech. = 1)
Management Score 2020	0.115**	−0.018	0.008	0.023	0.030	0.245**	0.265**
	(3.39)	(−0.28)	(0.35)	(0.56)	(1.44)	(3.14)	(3.29)
Log Labor Productivity 2020	−0.002	0.040**	0.008***	0.013	0.003	−0.018	−0.017
	(−0.54)	(2.46)	(4.90)	(1.09)	(1.39)	(−1.08)	(−1.00)
Any Other Technology						0.285***	
						(7.08)	
Observations	3,960	973	3,658	2,562	4,307	1,269	1,197
Adjusted R^2	0.012	0.084	0.004	0.003	0.004	0.043	0.025
Fixed Effects	Size, age, industry, and region						

Note: t-stats in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

MES-ABS: Other intangible capital

	Dependent Variable: Pr(AI = 1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Management Score 2020	0.272**	0.253**	0.271**	0.244**	0.425***	0.436***	0.461***	0.416***
	(0.0962)	(0.0954)	(0.0896)	(0.0865)	(0.110)	(0.1000)	(0.0970)	(0.111)
Log Labor Productivity 2020	−0.0245	−0.0153	−0.0343	−0.0246	−0.00811	0.00193	0.00452	0.0120
	(0.0216)	(0.0231)	(0.0193)	(0.0217)	(0.0339)	(0.0331)	(0.0407)	(0.0387)
Total Software 2022	1.40e−05			−7.34e−07				
	(1.82e−05)			(1.35e−05)				
R&D 2022		−0.113**		−0.114***				
		(0.0329)		(0.0266)				
Log Brand 2022			0.0249***	0.0247***				
			(0.00427)	(0.00347)				
Total Software 2021					9.15e−05**			8.22e−05**
					(3.30e−05)			(3.28e−05)
R&D 2021						−0.106***		−0.120***
						(0.0222)		(0.0162)
Log Brand 2021							0.0153	0.0127**
							(0.00813)	(0.00516)
Observations	514	514	470	470	472	472	427	427
Adjusted R^2	0.0342	0.0460	0.0521	0.0601	0.0560	0.0530	0.0548	0.0779
Fixed Effects	Size, age, industry, and region							

Note: t-stats in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness test: Outlier analysis

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)	(4) Pr(AI=1)	(5) Pr(AI=1)	(6) Pr(AI=1)
Management Score 2020 (Winsor 1%)	0.265**					
	(3.07)					
Management Score 2020 (Winsor 5%)		0.268**				
		(2.86)				
Management Score 2020 (Winsor 10%)			0.291**			
			(2.82)			
Management Score 2020				0.261**	0.262**	0.262**
				(3.08)	(3.11)	(3.11)
Log Labour Productivity 2020	−0.019	−0.019	−0.019			
	(−1.26)	(−1.25)	(−1.25)			
Log Labour Prod. (Winsor 1%)				−0.017		
				(−0.95)		
Log Labour Prod. (Winsor 5%)					−0.019	
					(−0.93)	
Log Labour Prod. (Winsor 10%)						−0.022
						(−0.95)
Observations	1,292	1,292	1,292	1,292	1,292	1,292
Adjusted R^2	0.024	0.024	0.024	0.023	0.023	0.023
Fixed Effects	Size, age, industry, and region					

Note: t-stats in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness test: Propensity score matching

	(1) P-Score	(2) NN(1)	(3) NN(3)	(4) IPW
ATET	0.102**	0.065*	0.061**	0.053*
	(2.05)	(1.73)	(2.41)	(1.90)
Potential Outcome Mean (Control)			0.275***	0.275***
			(12.50)	(10.83)
Observations	2,039	2,039	2,039	2,039
Fixed Effects	Size, age, industry, and region			

Notes: This table reports propensity score matching estimates of the effect of high management quality on AI adoption. High Management Score 2020 is a binary indicator for firms in the top half of the management score distribution. Column (1) reports kernel propensity score matching; column (2) reports nearest-neighbor matching with one neighbor; column (3) reports nearest-neighbor matching with three neighbors; column (4) reports inverse probability weighting. The potential outcome mean shows the predicted AI adoption rate for firms with low management scores. All specifications control for log labour productivity and include fixed effects for firm size, industry (2-digit SIC), firm age, and region. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness test: Propensity score matching

	(1) Pr(AI=1)	(2) Pr(Cloud=1)	(3) Pr(Robotics=1)	(4) Pr(S. Software=1)	(5) Pr(S. Equipment=1)	(6) Pr(Other tech.=1)	(7) Pr(AI=1 | Other tech=0)	(8) Pr(AI=1 | Other tech=1)
ATET	0.102**	0.035***	0.032	−0.004	−0.005	−0.004	0.087***	0.104***
	(2.05)	(3.22)	(0.53)	(−0.41)	(−0.34)	(−0.50)	(2.79)	(3.55)
Observations	2,039	6,091	1,587	5,668	4,012	6,640	2,008	1,886
Fixed Effects	Size, age, industry, and region							

Notes: This table reports average treatment effects on the treated (ATET) from propensity score matching, comparing firms with high management quality (top 50%) to those with low management quality across different technologies. Columns (1)-(6) examine AI, cloud computing, robotics, specialized software, specialized equipment, and any non-AI technology. Column (7) controls for general technology adoption; column (8) restricts the sample to firms that have adopted at least one other technology (Pr(AI=1 | ICT=1)). All specifications use nearest-neighbor matching with three neighbors and control for log labor productivity and fixed effects for firm size, industry (2-digit SIC), firm age, and region. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

From ONS Glossary

Artificial intelligence (AI)

AI is technology where computer programs or machines can learn from data and perform tasks usually done by humans. AI is currently used in a variety of ways, including:

- online product recommendations
- facial recognition
- self-driving vehicles
- medical diagnostic tools
- chatbots that interact in a conversational way and can answer complex questions