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Artificial intelligence, complementary assets and productivity: evidence from French firms

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Artificial intelligence, complementary assets and productivity: evidence from French firms

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Abstract

In this work we characterise French firms using artificial intelligence (AI) and explore the link between AI use and productivity. We relevantly distinguish AI users that source AI from external providers (AI buyers) from those developing their own AI systems (AI developers). AI buyers tend to be larger than other firms, while AI developers are also younger. The share of firms using AI is highest in the ICT sector, which exhibits a particularly high share of developers. Complementary assets, including skills, digital capabilities and infrastructure, play a key role for AI use, with AI buyers and developers leveraging different types of human capital. Overall, AI users tend to be more productive, however this appears largely related to the self-selection of more productive and digital-intensive firms into AI use. This is not the case for AI developers, for which the positive link between AI use and productivity remains evident beyond selection, suggesting a positive effect of AI on their productivity.

Keywords: Technology Diffusion, Artificial Intelligence, Digitalisation, Productivity.

JEL Codes: D20, J24, O14, O33.

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1 Introduction

Artificial intelligence (AI) is rapidly transforming economies and societies. It permeates several products and services used by consumers everyday, it is changing the demand for skills, and may play an important role to tackle societal challenges such as climate change. Relevantly, AI has the potential to boost the productivity of adopters (Brynjolfsson et al., 2018), allowing workers to operate more efficiently (Brynjolfsson et al., 2023), helping firms uncover new business opportunities or enabling new business models (Agrawal et al., 2022). However, empirical evidence comprehensively characterising AI diffusion across the economy and assessing how using AI affects firm efficiency is still at early stages, especially beyond the United States.[1]

In this work we characterise French firms using AI and explore the link between AI use and productivity. We leverage detailed survey microdata – collected by the French statistical office – that include comprehensive information on technology use in 2018, a period that precedes the recent boom in generative AI. We match this survey with firms' balance sheets that contain additional information on their characteristics and financials. The level of detail of these data and their representativeness of the French economy – differently from other commercial surveys – make them unique sources to analyse the patters of AI use among firms in great detail. In particular, the data allow to relevantly distinguish two different groups of AI users: firms sourcing AI from external providers (AI buyers) and those developing their own AI systems (AI developers).

Our contribution to the literature is threefold. First, we uncover a series of stylised facts concerning the diffusion of AI technologies in France, and in particular on the characteristics of different types of AI users. We focus on firm age, size and sectoral heterogeneity, first pooling together all AI users, and then distinguishing AI buyers from developers. We show that AI users tend to be overall younger and larger than other firms, in line with existing evidence (see for instance Zolas et al., 2020; Acemoglu et al., 2022), and that sectoral shares are highest in the ICT and professional services sectors. However, when we separate out AI buyers and developers, additional differences emerge. AI buyers are larger than other firms, whereas AI developers are also younger. Furthermore, the sectoral distribution of firms buying AI is significantly more homogeneous than the one of AI developers, which exhibit a particularly high share in the ICT sector. This may support the view that AI systems represent a general-purpose technology (GPT), given their more widespread diffusion among AI buyers, and the hypothesis that the development of AI is – at least partly – driven by a wave of high-tech young firms.

Second, we show that complementary assets play a key role for AI use. Focusing on various measures of firm digitalisation and human capital, we find that these are all positively and significantly related to AI use. AI use is indeed more likely among firms using larger bundles of business digital technologies (i.e., CRM, ERP and e-commerce), and it is thus likely fostered by the presence of a digital architecture within the firm through which business data can be more easily stored and managed. ICT skills (i.e., the employment of ICT specialists and the provision of ICT training to non-ICT personnel) and digital infrastructure (i.e., the use of a fast broadband connection) also play a critical role for AI use, consistently with the relevance of such complemetary assets for the digital transformation (see for instance Bresnahan et al., 2002; Chun,

[1] See for instance Acemoglu et al. (2022); Zolas et al. (2020); Alekseeva et al. (2021); Babina et al. (2021) for evidence on the US. A relevant exception is the cross-country analysis by Calvino and Fontanelli (2023), which is highly complementary to this country-specific paper. Additional literature is further discussed in the next section.

2003; Abowd et al., 2007). When distinguishing AI buyers from developers, results show that ICT training is associated with a higher probability of purchasing AI while the presence of ICT specialists is positively linked with AI development. This suggests that different types of AI users leverage different types of human capital. Furthermore, ICT skills, digital infrastructure and the use of other digital technologies appear to largely explain the size premium of AI buyers. AI developers remain instead larger than other firms even after accounting for these confounding factors.

Third, we analyse the relationship between AI use and productivity. On average, AI users tend to be more productive than other firms. This link tends to originate from large firms and to be more prominent in the ICT sector. However, this appears largely related to the selection of more productive highly-digital firms into the use of AI. Indeed, when considering all AI users together, the link disappears after controlling for complementary assets and past productivity. This is not the case for AI developers, for which the AI-productivity link remains significant beyond selection. This is robust to the inclusion of several confounding factors, highlighting a positive effect of AI on the productivity of developers, evident also when accounting for potential endogeneity issues using an endogenous treatment model. These results suggest that at this stage AI may not (yet) significantly boost productivity for all users, in line with the discussion by Brynjolfsson et al. (2018) and Agrawal et al. (2022). Investments in human capital and intangibles may take time before AI is successfully integrated into the activities of AI buyers, while AI developers – that already rely more significantly on specialised ICT skills – appear to already realise positive productivity returns.

These findings not only inform about the role of different factors – including complementary assets – enabling the digital transformation, but also help uncover whether and how firms translate AI adoption into productivity gains. This is instrumental to better understand how policy can foster a wide diffusion of AI and its returns across firms and sectors, ensuring an inclusive digital transformation.

The remainder of the paper is organised as follows. In Section 2 we review recent contributions to the literature related to AI use by firms, focusing on those more related to our paper. In Section 3 we discuss in detail about the data sources used in this work, the French ICT survey and balance sheet data, and provide a series of basic summary statistics of the main variables used. In Section 4 we focus on the characteristics of firms using AI vis-à-vis those of other firms and explore the role of complementary assets. In Section 5 we analyse the relation between the use of AI and productivity, using different empirical models. In Section 6 we discuss the implications of our analysis and the channels linking AI use and productivity. Finally, in Section 7 we draw some conclusions and point to next steps for future analysis.

2 Existing evidence on AI use by firms

Studies on AI use by firms primarily rely on US data and are mainly based on three data sources: firm-level ICT surveys, online job posting data that contain information on AI skills demand, and Intellectual Property (IP) records, in particular patents.[2] The literature more closely related to the current analysis on AI use by

[2] Recent contributions to the literature have also used other proxies of digital investments such as automation shocks or IT expenditures (see e.g. Jin and McElheran, 2018; Acemoglu and Restrepo, 2020; Aghion et al., 2020; Domini et al., 2021, 2022), which – although related – do not only proxy for AI use by firms but have instead a broader nature. Recently the literature has also used information from online websites to identify and characterise companies and organisations

firms highlights four key facts.

First, the diffusion of AI technologies is still limited and heterogeneous across sectors. Evidence from ICT surveys carried out in 2018 in the United States, Germany and Korea (Zolas et al., 2020; Rammer et al., 2022; Cho et al., 2022), from matching different data sources in the United Kingdom (Calvino et al., 2022) and from recent cross-country analysis (Calvino and Fontanelli, 2023) shows that the use of AI technologies is still rare and concentrated in the ICT and professional services sectors. Similarly, AI-related innovation are concentrated in high-tech sectors (Santarelli et al., 2022) and the demand for AI-related jobs is prevalent in ICT, consulting and financial/insurance sectors (Alekseeva et al., 2021).[3] However, the demand for AI-related jobs has been growing at a fast pace in the last decade in the United States (Acemoglu et al., 2022; Alekseeva et al., 2021; Babina et al., 2021) and in several other advanced countries (Canada, Singapore, the United Kingdom, see Squicciarini and Nachtigall, 2021).[4] The number of AI-related skills per posting has been growing as well (Squicciarini and Nachtigall, 2021), hinting at how the diffusion of AI technologies is increasingly embedded in firms' development processes.

Second, existing evidence highlights a positive relation between AI adoption and firm size, which can be driven by both self-selection of larger firms into AI use and by a positive effect of AI on firm size. In the US, the share of AI users monotonically increases with size (Zolas et al. 2020, see also Rammer et al. 2022 for Germany, Calvino et al. 2022 for the United Kingdom, and Calvino and Fontanelli 2023 for a cross-country analysis). Ex-ante larger firms, with higher cash holdings and R&D investments, also demand more intensively AI skills (Alekseeva et al., 2021; Babina et al., 2021). The self-selection of larger firms into AI use can be explained by scale advantages related to the availability of high computing power, massive amount of data and, more in general, of intangibles related to AI, which are necessary to reap the full benefits of AI technologies (Brynjolfsson and McAfee, 2014; Brynjolfsson et al., 2021). If the spread of cloud technologies helped enhance SMEs' computing power also raising their productivity (DeStefano et al., 2019), more limited access to data or lack of complementary intangibles may hinder the diffusion of AI technologies in SMEs, which tend to be less digitalised (Zolas et al., 2020) and more financially constrained (Hadlock and Pierce, 2010). However, part of the literature suggests that the relation between AI use and size is not exclusively limited to self-selection, as AI adoption also has a positive impact on firm size in the US (see Babina et al., 2021). AI-related innovations raise firm sales and employment growth (Alderucci et al., 2021; Damioli et al., 2023) and investments in AI-related skills have a positive, but not immediate, effect on sales and employment, which is driven by product innovations stemming from AI use and grows with firm size (Babina et al., 2021). Accordingly, the diffusion of AI technologies may strengthen the increasing trends in industry concentration (see Bajgar et al., 2019, 2021), trigger winner-takes-most dynamics (Korinek and Stiglitz, 2018), also raising barriers to entry.[5] From this perspective, scale advantages in AI adoption may also strengthen secular declines

with an AI-related online presence (Dernis et al., 2023). Concerning ICT surveys, these are typically conducted by statistical offices. However there is a part of literature that examines ICT survey data collected by other institutions (see for instance Cette et al., 2022; Bessen et al., 2022; Czarnitzki et al., 2022; Cirillo et al., 2023).

[3]The demand for AI-related jobs is typically measured using proxies of AI-related skills/occupations based on online job vacancy data from Lightcast (see Acemoglu et al., 2022; Squicciarini and Nachtigall, 2021; Alekseeva et al., 2021; Babina et al., 2021). The financial and insurance sectors are usually not covered by ICT surveys.

[4]A surge in AI-related patenting activity took place in parallel (Dibiaggio et al., 2022), suggesting that the increase in AI-related demand may be – at least partially – driven by firms engaged in R&D activities.

[5]See also Calvano et al. (2020); Calzolari et al. (2023) for a discussion about the challenges of algorithmic pricing and

in business dynamism, which are already strong in digital-intensive sectors (see Calvino and Criscuolo, 2019; Calvino et al., 2020).[6]

Third, some analyses suggest that a wave of high-tech young firms has been driving – at least partly – the development of AI technologies, notwithstanding the role of high entry costs for AI startups (for instance, in terms of proprietary data, see Bessen et al., 2022). Cross-country evidence from 11 OECD countries suggests that older firms tend to be less likely to adopt AI (Calvino and Fontanelli, 2023). Complementary findings for the US show that firms using AI are more likely younger (Acemoglu et al., 2022). Focusing on the UK, Calvino et al. (2022) also show that firms that have AI at the core of their business tend to be young. Relatedly, venture capital investments in AI startups has been significantly growing over time (Tricot, 2021), in line with the existence of a generation of AI start-ups.

Finally, the relation between firm productivity and AI use is still unclear.[7] Using measures of AI skills, Babina et al. (2021) find no effect of AI on the growth of sales per worker or of TFP. A positive impact of AI-related innovations (i.e., patents) has been instead found on the productivity of SMEs and service firms and on the output and costs per worker in a dataset including worldwide patenting firms (Damioli et al., 2021) and on the output per workers of US patentees (Alderucci et al., 2021). When considering ICT surveys, Czarnitzki et al. (2022) find a positive impact of AI on German firms' productivity. However, employing the 2019 wave of the Annual Business Survey, Acemoglu et al. (2022) show that the relation between labour productivity and AI use does not appear significant for US firms. Finally, Calvino and Fontanelli (2023) show that the productivity premia of AI users tend to disappear – or to reduce – in several OECD countries when the role of assets and technologies complementary to AI use is taken into account. This evidence seems to clash against studies finding a positive effect of ICT and digitalisation on productivity at the firm level (Crouzet and Eberly, 2019; DeStefano et al., 2019; DeRidder, 2019; Hsieh and Rossi-Hansberg, 2021), but it may be consistent with the existence of a J-curve in productivity following the adoption of AI (Brynjolfsson et al., 2021). It is indeed likely that AI systems require a series of complementary investments in intangibles that need more time before they can translate AI use into productivity gains. It is also possible that the early phase of adaptation of AI to existing development processes is characterised by uncertainty and experimentation. Furthermore, the use of AI by firms may need a restructuring of their whole structure, rather than of just one of its parts (Agrawal et al., 2022). Accordingly, the effect of AI adoption on productivity may take time before materialising and the early phases of AI use may even be characterised by a decrease in productivity due to crowding out dynamics. It may be thus too early to find an effect of AI adoption on firm productivity (Acemoglu et al., 2022). The conjectures on the existence of complementarities related to AI is supported by studies on AI-related patents.

AI-powered recommendations for competition.

[6]A broader stream of literature focuses on the role of AI for employment (see for instance Aghion et al., 2019; Lane and Saint-Martin, 2021; Felten et al., 2021; Acemoglu et al., 2022; Babina et al., 2023). This stream of research is however less related to the scope of the current analysis.

[7]A recent wave of works tends to find a positive impact of generative AI on workers' productivity (see also Brynjolfsson et al., 2023; Noy and Zhang, 2023; Peng et al., 2023; Eloundou et al., 2023; Kreitmeir and Raschky, 2023). However, the direction of such relation seems to depend on the extent to which tasks are within or outside the current capabilities of AI systems (Dell'Acqua et al., 2023). This evidence is complementary to our work. Indeed, the use of generative AI by workers is just one of the types of AI systems that can be adopted by firms. Furthermore, these analyses often refer to specific categories of workers (e.g., customer support agents in Brynjolfsson et al., 2023 and developers in Peng et al., 2023; Kreitmeir and Raschky, 2023 or consultants in Dell'Acqua et al., 2023). Finally, the extent to which AI-driven increases in workers' productivity translate into firms' productivity needs still to be explored.

Santarelli et al. (2022) highlight how AI-related patents are strongly rooted in ICT and robot knowledge bases. Igna and Venturini (2023) study patent applications filed at the EPO and find that AI innovators have likely developed past innovations in AI or related technology fields such as ICTs. The literature on the relevance of AI complementary assets is, at our knowledge, so far still limited (see Brynjolfsson et al., 2021).[8]

3 Data

Our analysis is based on microdata from the 2019 French ICT survey (*"Enquête sur les Technologies de l'Information et de la Communication (TIC)"*).[9] The survey is administered by INSEE (the French statistical office). It consists of a rotating sample of about 9000 firms from manufacturing and market-services sectors with questions related to the use of advanced digital technologies in 2018.[10] The sample is representative of the population of firms with employment greater than or equal to 10 and is exhaustive for firms with more than 500 employees. These data are characterised by a unique level of detail and representativeness compared to other commercial surveys, which allow an in-depth analysis of AI adoption patterns among firms. Furthermore, they can be easily merged with other sources of French firms' data thanks to the *Siren* code, which uniquely identifies French companies.

Part of the ICT survey is dedicated to questions on AI use by firms. In particular, firms are asked whether they used AI technologies in 2018.[11] Our main AI use variable takes thus the form of a dummy, which indicates whether firms use AI technologies or not. The data relevantly allow to separate out AI users into AI buyers vis-à-vis AI developers. In particular, AI buyers are firms using AI technologies developed by external providers, while AI developers use AI systems developed in-house.

The ICT survey also includes questions on the use of other business digital technologies or tools, including the use of Costumer Relation Management (CRM), Enterprise Resource Planning (ERP) software, and regarding e-commerce activities. We count the number of these business digital technologies to build the variable "Number of digital technologies", which takes values equal to the number of technologies used by the firm (from 0 to 3) and represents a proxy for its level of digitalisation.[12] In the survey, firms are also asked about the presence of ICT specialists. We use this variable as a proxy for the presence of digital skills within the firm. In this respect, we also use the presence of ICT training for non-ICT specialists, as firms relying on new AI technologies may also need to leverage complementarities between those and the skills of the existing workforce. Finally, we use the speed of the broadband connection as a measure of digital infrastructure. In particular, we build a dummy for the presence of a fast broadband connection, which takes value equal to 1 in presence of a speed greater or equal to 100 mbit/second.[13]

[8]Beyond AI use and its returns, the role of complementarities in the innovation, production and organisational structure of firms is discussed for instance by Bianchini et al. (2018); Tambe et al. (2020); Calvino et al. (2022); Costa et al. (2023).

[9]Further information about the survey can be found here.

[10]The questions on advanced digital technologies change on an yearly basis.

[11]Firms are asked the following question: "In 2018, did your company make use of software and/or equipment incorporating artificial intelligence technologies?".

[12]Business digital technologies are less likely to be related to sectoral specificities than other advanced technologies, whose use may be largely sector specific. For example, Robots and 3-D Printers are more likely to be used in manufacturing than in consulting services and would not be useful in identifying a more general proxy of firm digitalisation.

[13]In the 2019 wave of the ICT survey this is the highest speed included among the possible choices in the question

We match the ICT survey with French firms' balance sheet data (FARE) between 2011 and 2019.[14] This data allow us to gather information on firm sales, age, employment and value added (i.e., sales net of intermediate costs) and to compute a proxy of labour productivity as the ratio of value added to the number of workers employed by the firm.[15] Concerning employment and age, we divide firms in four employment classes (see also Acemoglu et al., 2022), small (<20 employees), medium-small (20-49 employees), medium-large (50-249 employees) and large (>249 employees), and in 3 age classes, young (<6 years old), mature (6-10 years old) and old (>10 years old). This distinction allows us to understand how different types of firms are linked to the use of AI technologies.[16]

We also group firms using the sectoral aggregation reported in Table 1. This aggregation is aimed at capturing common features between sectors and encompasses eight different macro-sectors (Manufacturing, Construction, Wholesale & Retail, Transport & Storage, Accommodation & Food, Information & Communication Technologies, Professional & Scientific Activities, Administrative & Real Estate).

Group of sectors	Sector 2–digit code (ISIC rev.4)
Manufacturing & Utilities	10-33
Construction	41-43
Wholesale & Retail	45-47
Transport & Storage	49-53
Accommodation & Food	55-56
Information & Communication	58-63, 951
Professional & Scientific Activities	69-75
Administrative & Real Estate	68; 77-82

Table 1: The sectoral disaggregation used for computing shares.

All the regressions and summary statistics reported in this work have been weighted using probability weights available in the ICT survey. Monetary variables have been deflated, as previously mentioned.

Based on the database described above, we report on Table 2 a series of summary statistics, which also allow for a first basic (unconditional) comparison of AI users, buyers and developers with other firms. AI users, buyers and developers are on average larger and more productive than their counterparts. They also more likely employ ICT specialists and provide ICT training to their workers. The presence of a fast broadband connection is more likely in AI firms, which are characterised by a higher average use of digital technologies other than AI. Finally, AI developers are younger than other firms, whereas AI buyers and AI users (when considered altogether) are very close in terms of age.

about broadband connection speed.

[14]Further information about FARE data can be found here.

[15]Data on sales and value added are in real terms and have been deflated at the 2-digit sector level.

[16]Using size and age classes instead of their respective continuous counterparts may provide relevant advantages (see also Acemoglu et al., 2022). First, the presence of AI fixed costs is more clearly captured by size classes, as these may act as a threshold for adoption. Second, endogeneity issues are likely mitigated with respect to the use of a continuous variable when exploring its relation with productivity. Third, the year of birth of the oldest firms in the sample may be imprecise and using age class dummies allows to tackle possible measurement errors. The key findings of the current analysis do not depend on this choice, as corroborated by unreported regression analyses using firm size and age as continuous variables.

	All firms	AI User		AI Buyer		AI Developer	
		User	Non-User	Buyer	Non-Buyer	Developer	Non-Developer
Age	24	24	24	24	24	21	24
Productivity	64000	70000	64000	68000	64000	92000	63000
Employment	63	154	51	137	55	268	56
ICT Specialists	0.17	0.30	0.16	0.23	0.17	0.59	0.16
ICT Training	0.19	0.28	0.18	0.25	0.18	0.40	0.18
Fast Broadband Connection	0.13	0.21	0.12	0.19	0.13	0.36	0.12
Number of digital tech.	0.90	1.16	0.86	1.11	0.88	1.54	0.88

Table 2: Averages for the whole sample and classifying firms by AI type. Age and employment statistics have been rounded to the closest unity, productivity to the closest thousand.

4 The characteristics of AI adopters

In this section we discuss the main characteristics of AI users in the database – disentangling between AI buyers and AI developers – and focus on the role of complementary assets, such as digital infrastructure, skills, and other digital technologies for AI use. French AI users account for 11.4% of French firms with more than 10 employees. The use of AI technologies is thus still limited, but probably slightly higher than in some other countries (see the discussion in Section 2, although the comparison may be challenging given differences in timing and definitions). There is however a considerable difference between AI buyers and developers, that represent respectively 9.9% and 3.2% of French firms with more than 10 employees.[17]

When focusing on sectoral shares (see Figure 1), a highly uneven distribution of AI actors across sectors emerges. The share of AI users is highest in the Information & Communication (26.1%) and in the Professional & Scientific services sectors (16.7%), whereas other sectors tend to lag behind in terms of diffusion. Again, distinguishing between AI buyers and AI developers reveals significant heterogeneity. Even though the highest shares of AI users, buyers and developers are always in the ICT sector, the gap between ICT and other sectors is remarkably high for developers. Conversely, the sectoral shares of firms buying AI technologies from third parties tend to be more homogeneous, which support conjectures about the general-purpose nature of AI technologies. The sectoral heterogeneity in adoption shares also suggests that users developing their own AI or buying from third parties are different. The fact that the sectoral gap between AI developers is the highest in the ICT sector is consistent with the necessity of advanced ICT and technical skills to develop AI systems, that workers in other sectors may not have.

Focusing on the characteristics of AI firms, we report the shares of AI users, buyers and developers by size and age classes in Figures 2 and 3 respectively. The relation between size and AI use is positive, with the largest firms (with more than 249 employees) exhibiting about two times the share of AI use than the smallest ones. Also considering the high fixed costs possibly characterising AI-related and complementary investments

[17]Some firms are both AI buyers and AI developers, this is why the sum of shares of AI buyers and developers is higher than the overall share of AI users. This way of grouping AI users allows for both a simple setting in the regression analyses and to focus on groups of firms that are large enough to assess relevant information. Additional analysis using an alternative grouping of i) only AI buyer, ii) only AI developer and iii) both AI buyer and developer is discussed in Section 6.

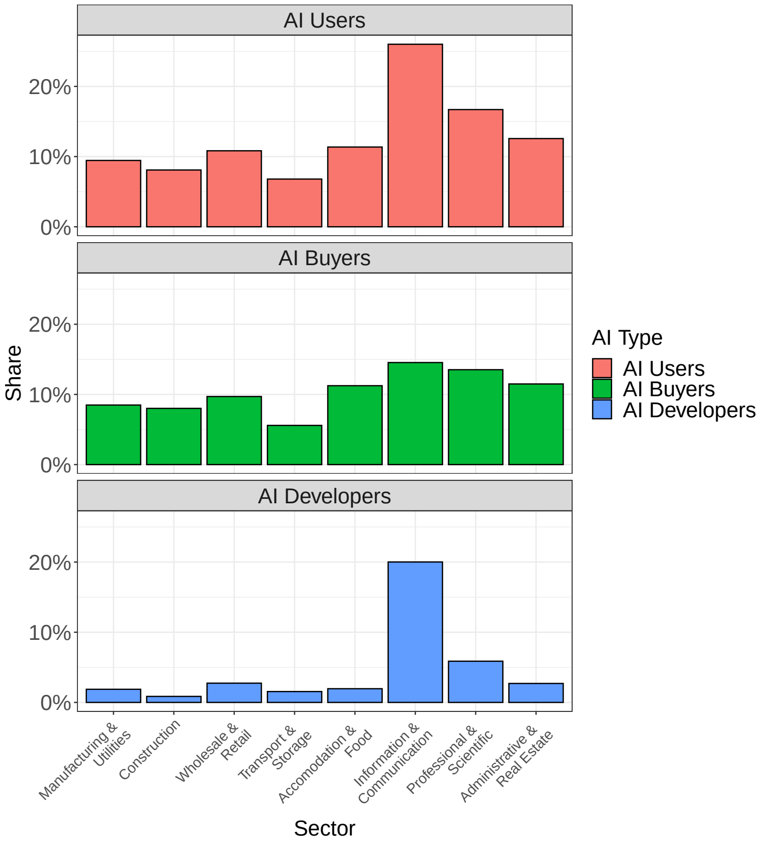

Figure 1: Shares of AI users, buyers and developers by sector (see Table 1).

Figure 2: Shares of AI users, buyers and developers by size class.

(Brynjolfsson et al., 2021), the AI use-size relation may be related to firm diversification, digital intensity, larger amount of data to leverage AI applications or lower financing constraints. Larger and more diversified firms may more easily find applications for AI technologies, they may have access to larger amount of data needed to fully leverage AI applications or may face lower costs to access external financing. More digitalised firms may be more at ease in upgrading to advanced digital technologies, such as AI, thanks to their higher availability of (or capability to use) intangibles or other complementary assets. Also, the association between AI use and firm size seems stronger for AI developers than for AI buyers, suggesting again that drivers of AI use by firms may differ by the source of AI technologies. The development of AI technologies may be more ICT intensive than the use of an existing AI technology because it may require more in-depth ICT skills and

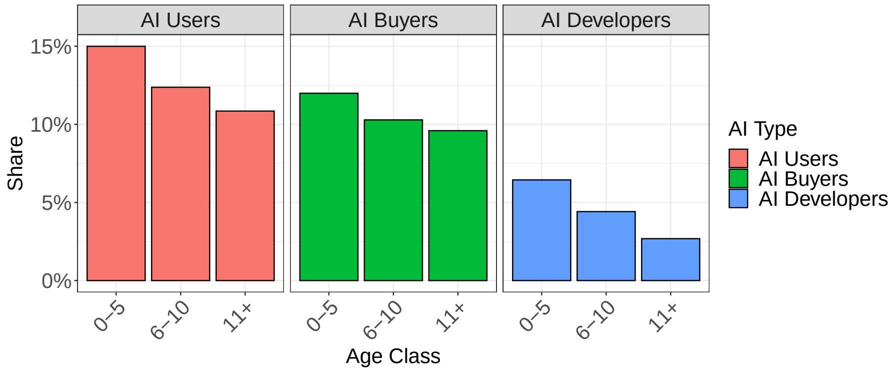

Figure 3: Shares of AI users, buyers and developers by age class.

thus more investments in intangibles. Differently from size, the relation between AI use and age is negative. This is noteworthy, because in general size and age are positively correlated. Younger firms are more likely AI users, possibly suggesting a role of new managerial and technical skills or new business models. Furthermore, young firms often introduce more radical innovations, especially when new technological paradigms – such as the one brought by AI – emerge. Again, the relation between AI use and age seems stronger in the case of AI developers, in line with the summary statistics in Table 2.

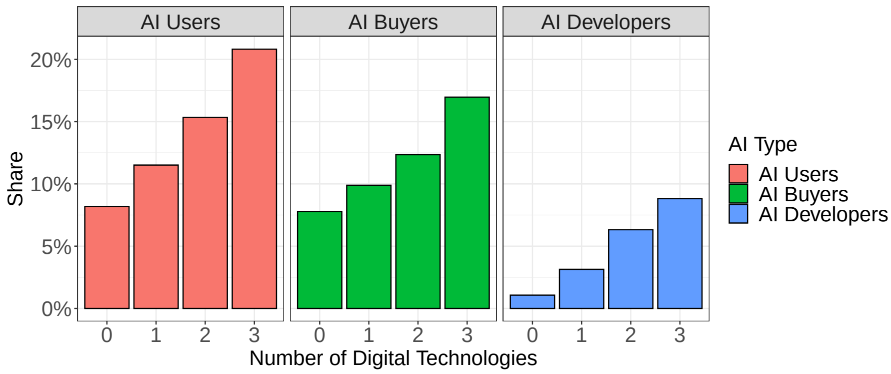

Figure 4: Shares of AI users, buyers and developers by number of digital technologies.

Finally, we focus on the shares of AI users by number of business digital technologies adopted in Figure 4. Firms using a higher number of digital technologies are also more likely to be users, buyers and developers of AI. This highlights the presence of relevant complementarities between the use of AI and other digital technologies, as firms may be required to build a proper digital architecture in order to exploit business data to use AI systems.

Although already informative, the descriptive (unconditional) patterns presented above may be potentially influenced by a number of confounding factors that are not accounted for. This is why we turn to a regression analysis that further takes those into account. First, the relations discussed above may depend on the sectoral composition, such as the possible concentration of AI users in sectors in which average age is lower. Second, regressions may help further disentangle the role of other confounding factors affecting the use of AI, in particular considering intangibles, skills, digital infrastructure together and beyond the role of

Characteristics of AI Users, Buyers and Developers - Logit Regression Estimation

		AI Users			AI Buyers			AI Developers	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Size class, 20-49	-0.00344	-0.00851	-0.0134	-0.00672	-0.00950	-0.0134	0.000237	-0.00290	-0.00525
	(0.0107)	(0.0107)	(0.0107)	(0.0102)	(0.0102)	(0.0102)	(0.00578)	(0.00585)	(0.00588)
Size class, 50-249	0.0130	-0.00884	-0.0187	0.00219	-0.00913	-0.0172	0.0134**	0.000219	-0.00417
	(0.0111)	(0.0119)	(0.0121)	(0.0110)	(0.0116)	(0.0118)	(0.00525)	(0.00604)	(0.00600)
Size class, 250+	0.0714***	0.0239*	0.0114	0.0442***	0.0178	0.00772	0.0419***	0.0173***	0.0112*
	(0.00995)	(0.0129)	(0.0131)	(0.00981)	(0.0125)	(0.0127)	(0.00462)	(0.00633)	(0.00633)
Age class, 6-10	-0.0204	-0.0232	-0.0240	-0.0151	-0.0170	-0.0177	-0.00843	-0.00997	-0.00974
	(0.0197)	(0.0195)	(0.0195)	(0.0194)	(0.0194)	(0.0193)	(0.00901)	(0.00903)	(0.00918)
Age class, 11+	-0.0329**	-0.0336**	-0.0350**	-0.0198	-0.0210	-0.0222	-0.0243***	-0.0239***	-0.0240***
	(0.0166)	(0.0162)	(0.0162)	(0.0162)	(0.0161)	(0.0161)	(0.00797)	(0.00793)	(0.00807)
ICT Specialists		0.0442***	0.0329***		0.0155	0.00641		0.0332***	0.0276***
		(0.0118)	(0.0119)		(0.0122)	(0.0122)		(0.00609)	(0.00606)
ICT Training for Other Employees		0.0272**	0.0235**		0.0222**	0.0191*		0.00479	0.00320
		(0.0108)	(0.0107)		(0.0106)	(0.0105)		(0.00472)	(0.00467)
Fast Broadband		0.0328***	0.0275**		0.0268**	0.0225**		0.0124***	0.0102**
		(0.0112)	(0.0111)		(0.0112)	(0.0111)		(0.00461)	(0.00464)
Number of Digital Technologies			0.0240***			0.0193***			0.0119***
			(0.00531)			(0.00516)			(0.00273)
Observations	8,588	8,588	8,588	8,588	8,588	8,588	8,588	8,588	8,588
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0340	0.0438	0.0496	0.0189	0.0231	0.0276	0.146	0.179	0.192

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

Table 3: Logit regressions employing the AI User (Models 1-4), AI Buyer (Models 5-8) and AI Developer (Models 9-12) dummy as dependent variable.

the firm characteristics explored above. We therefore estimate the following Logit regression:

$$\mathrm{AI}_{i,t}^{\mathrm{Type}} = f(\mathbf{Size}_{i,t}; \mathbf{Age}_{i,t}; \mathbf{ICT\ Skills}_{i,t}; \mathbf{Digitalisation}_{i,t}; \mathbf{X}_{i,t}) \tag{1}$$

Where $\mathrm{AI}_{i,t}^{\mathrm{Type}}$ is a dummy variable that equals one if a firm uses, buys or develops AI (the first type focuses on all AI users, the second one on AI buyers, and the third one on AI developers), $\mathbf{Size}_{i,t}$ is a vector of size class dummies based on the number of employees (20-49, 50-249, 250+), $\mathbf{Age}_{i,t}$ is a vector of age class dummies based on firm age (6-10, 11+),[18] $\mathbf{ICT\ Skills}_{i,t}$ includes dummy variables indicating the presence of ICT specialists and of ICT training for non-ICT employees, $\mathbf{Digitalisation}_{i,t}$ refers to a dummy variable that equals one if the firm uses a fast broadband connection and to a variable recording the number of other business digital technologies used (ERP, CRM, e-commerce), and $\mathbf{X}_{i,t}$ is a vector of controls including industry and geographic fixed effects.[19]

We report the results of the estimation of Equation 1 in Table 3, which includes the estimated marginal effects from the Logit regressions using dummies for AI users, buyers and developers as dependent variables. The baseline regression model (Model 1 in Table 3) shows that in absence of other controls, large (250+) firms have a higher probability of AI use, while older ones (with more than 10 years) have a lower probability of using AI, in line with the previously presented descriptive evidence. Distinguishing between AI buyers and developers confirms that, for both groups, being a large firm is associated with a higher probability of AI use (Models 4 and 7). However, being a young firm appears to be related only to the probability of AI development, given the negative and significant coefficient of the older age dummy for this group of firms. This seems to drive the overall result on the role of age class evident for all AI users (in Model 1) and may suggests the possible existence of barriers to AI development by more mature firms within the same size bins.

The link between firm size class and AI use tends to lose significance when accounting for other complementary factors, in particular when controlling for fast broadband connection, other digital technologies, ICT specialised workforce and training for non-ICT workers. This suggests that scale advantages in the adoption of AI technologies are at least partially driven by the joint presence of proper digital infrastructures, of a firm digital architecture and of ICT skills. In particular, the largest size dummy coefficient becomes not significant when considering all AI users together (see Model 3 in Table 3) and AI buyers (Models 5 and 6), but its significance tends to remain in the AI developer case (Models 8 and 9) – even though moving from 1% to 10%. This may hint at the presence of further drivers of AI development related to firm size – and therefore to fixed costs – with respect to the ones of AI buyers. These may be concern for example the need of large amounts of data to develop and train large-scale AI systems or to costs related to acquiring computing power, as conjectured by Brynjolfsson and McAfee (2014).

Focusing on the coefficients of complementary assets suggests that these are crucial for AI use. Digital infrastructure is key to foster AI diffusion, as highlighted by the positive association between the presence of a fast broadband connection and the use of AI, which is significant throughout all regressions. The positive

[18] The reference category for size dummies is the class of firms with less than 20 employees. The reference category for age dummies is the class of firms with less than 6 years. For robustness, we also tested an alternative model that includes the logarithm of size and age instead of their respective classes. The main results are confirmed.

[19] Industry fixed effects are based on the OECD STAN A38 classification. More information can be found by opening this link. Geographic fixed effects correspond instead to French regions.

and significant coefficient of the number of digital technologies suggests that firms may leverage digitalised business information to adopt AI, highlighting that AI is complementary to the overall degree of firm digitalisation.

While the use of a fast broadband connection and the number of digital technologies adopted are always significant, the positive relation between ICT specialists, ICT training and AI use depends on the type of AI users considered. In particular, the presence of ICT specialists is only linked to the use of AI when it is developed by the firm, whereas the training of non-ICT specialists is significant for AI buyers and not for AI developers. Albeit both suggest the importance of ICT skills for the diffusion of AI technologies (also see Babina et al., 2023), this result hints at the relevance of different skills for firms developing vis-à-vis buying AI systems. On the one hand, the development of AI requires a more in-depth knowledge of AI algorithms, and therefore ICT specialists may be more needed. On the other hand, use of ready-made AI systems may only require workers to know which inputs are needed to interact with AI systems in order to interpret their outputs, without necessarily a comprehensive understanding of the whole process behind them.

5 AI use and productivity

In this section we investigate the relation between AI use and productivity. We do so by estimating a series of regressions that employ the logarithm of productivity as dependent variable and AI use as main explanatory variable.

We organise the discussion in three sub-sections. In Section 5.1 we discuss the results of productivity regressions focusing on all AI users. By doing this, we seek to understand whether on average there is a link between AI use and productivity and, if this is present, on which grounds it can be explained. We then explore in Section 5.2 the extent to which the AI-productivity nexus is heterogeneous across firms of different size or belonging to different sectors, and among different types of AI users – AI buyers and developers. Finally, we address endogeneity issues in the AI-productivity link in Section 5.3 by estimating an endogenous treatment model.

5.1 Productivity regressions: focusing on all AI users

In this section we investigate the link between AI use and productivity by estimating the following regression model:

$$\text{Log-Productivity}_{i,t+1} = \alpha + \beta_1 \text{AI}^{\text{User}}_{i,t} + \beta_2 \text{Initial Log-Productivity}_i + \beta_{\mathbf{X}} \mathbf{X}_{i,t} + \epsilon_i \tag{2}$$

where $\text{Log-Productivity}_{i,t+1}$ is the logarithm of labour productivity (i.e., the ratio of real value added to the number of employees), $\text{AI}^{\text{User}}_{i,t}$ is the dummy variable indicating whether a firm uses AI or not (including both AI buyers and developers), $\text{Initial Log-Productivity}_i$ is the productivity level either in 2011 or in the birth year of the firm (when later than 2011), $\mathbf{X}_{i,t}$ is a vector of controls, which includes 2-digit industry and geographic fixed effects, size and age class dummies, other digital technologies and ICT skills. We include initial productivity in the regression model because it allows to isolate the association between AI and productivity after

Productivity Regression for AI Users

	Model 1	Model 2
AI User	0.0467*	0.0266
	(0.0280)	(0.0282)
Size class, 20-49	-0.00188	-0.0321*
	(0.0178)	(0.0170)
Size class, 50-249	-0.00626	-0.0987***
	(0.0215)	(0.0224)
Size class, 250+	0.0638*	-0.123***
	(0.0349)	(0.0386)
Age Class, 6-10	0.0471	-0.0236
	(0.0390)	(0.0404)
Age Class, 11+	0.128***	-0.0996***
	(0.0339)	(0.0341)
ICT Specialists		0.0993***
		(0.0253)
ICT Training for Other Employees		0.0376*
		(0.0215)
Fast Broadband		0.136***
		(0.0236)
Other Digital Technologies		0.0334***
		(0.00920)
Initial Log-Productivity		0.297***
		(0.0200)
Observations	8,392	8,392
Adj. R^2	0.232	0.373
Industry Fixed Effects	Yes	Yes
Geographic Fixed Effects	Yes	Yes

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

Table 4: OLS estimates of regressions using the logarithm of productivity in 2019 as dependent variable and AI use as main explanatory variable.

accounting for firm productivity at a moment (2011) in which AI use was very unlikely.[20] The inclusion of the initial productivity term is also aimed at controlling for selection of most productive firms into AI use. This is relevant because the data do not contain information on the date of first use/adoption of AI.

We report the results of the productivity regressions using firm-level productivity in 2019 as dependent variable and AI use as main explanatory variable in Table 4. We perform these regressions with and without initial productivity and controls other than industry, geographic, size and age fixed effects. On average, AI use is significantly linked to firm labour productivity (Model 1 in Table 4), but the relation loses significance when the regression controls for ICT skills, fast broadband connection, number of digital technologies and initial productivity, whose coefficients are all positive and significant (Models 2 in Table 4).[21]

[20]We chose to use 2011 as the year in which initial productivity is computed as this is a moment in which AI systems were likely not used by firms. In fact, several significant improvements in AI applications and technologies took place in 2012 (e.g., AlexNet neural network) and after that the use of deep learning and artificial neural networks started to outperform state-of-the-art non-AI related techniques in statistical analyses (see also here, here and Babina et al., 2021). Accordingly, the boom in AI use by firms very likely started after 2011 in the US, and probably even later in other countries, such as France. The main results are robust to different base year specifications for the initial productivity term (e.g., 2010).

[21]The link between these assets and productivity is in line e.g., with the findings by Harrigan et al. (2023) or Cette et al. (2022).

The absence of a significant AI-productivity link after accounting for complementary assets and initial productivity supports the hypothesis of firm selection into AI use, suggesting that the the positive association found in Model 1 has not been driven by AI adoption. Furthermore, in presence of other controls, the largest size class and the age dummies switch sign, becoming negative. Concerning size, our result hints at the relevance of intangibles, digital tools and investments for boosting firm productivity and at their greater availability in larger firms. The sign change of the largest size class coefficient may thus be explained by lower productivity increases experienced by larger firms once the role of initial productivity and other complementary assets is accounted for. Similarly, older firms tend to be more productive, but their productivity may thus grow less than younger firms when accounting for initial productivity and other complementary assets.

5.2 Heterogeneity in the AI-productivity link

The findings presented in Section 5.1 have focused on the relation between AI and productivity in the overall sample, before and after accounting for initial productivity and the role of complementary assets. The positive link between AI use and productivity disappears once controlling for such factors, supporting the hypothesis of self-selection of more digital-intensive and productive firms into AI use. Here we further explore the heterogeneity in the AI-productivity relation. More specifically, we focus on the two firm characteristics that are mostly related to AI – size and sector (see Section 4) – and on the different types of AI users (i.e., AI buyers and developers), which leverage on different ICT skills (see again Section 4).

In particular, in Table 5 we estimate Equation 2 by interacting the AI use and the size class dummies. This regression allows to further explore the extent to which the link between AI use and productivity may depend on firm size classes. A positive and significant relation emerges when AI use is interacted with the dummy variable identifying large (250+) firms (Model 1 in Table 5), suggesting that either gains from AI are captured by largest firms or that larger (possibly more productive) firms self select into AI adoption. Scale advantages may be related for instance to the availability of larger amount of data to leverage AI applications or to more considerable endowments or capabilities to use intangibles and other assets complementary to AI. Accounting for such complementary assets, once again, may allow to further investigate the origin of the AI-productivity link. In fact, similarly to Model 2 of Table 4, the significance of the interaction disappears when initial productivity and complementary assets are accounted for (see Model 2 in Table 5). This suggests that although the positive association of AI use with productivity tends to originate from large firms, this appears related to the role of complementary assets and to their initial productivity.[22]

In order to further investigate the AI-productivity nexus, we also estimate the main regression model (see Equation 2) on sectoral sub-samples based on the decomposition in Table 1 and we report results in Table 6. The sector-level regressions may allow to better understand the sectoral origins of the AI-productivity relations. Indeed, the nexus between AI use and sector-specific organizational and productive structures may

[22]Furthermore, the interactions between AI use and smaller size classes tend to become more negative, with the one with the 20-49 size class that becomes significant. This may be due to the presence of a productivity J-curve induced by AI adoption, where small non-adopter firms (i.e., the reference category) do not experience the negative impact on productivity to which AI users may be subject and that are captured by the AI-size interactions. Furthermore, as size grows, the interactions coefficients tend to increase, losing significance and turning positive for the largest size class This may be due to size being positively linked with the amount of complementary assets, whose availability mitigates possible negative effects of AI adoption on productivity (Brynjolfsson et al., 2018).

Productivity Regression for AI Users – Heterogeneity by size

	Model 1	Model 2
AI User	0.0634	0.0743
	(0.0458)	(0.0469)
Size class, 20-49	0.00365	-0.0204
	(0.0187)	(0.0174)
Size class, 50-249	-6.65e-05	-0.0856***
	(0.0219)	(0.0224)
Size class, 250+	0.0371	-0.135***
	(0.0408)	(0.0431)
AI*Size class, 20-49	-0.0513	-0.109*
	(0.0610)	(0.0610)
AI*Size class, 50-249	-0.0520	-0.116
	(0.0769)	(0.0766)
AI*Size class, 250+	0.119*	0.0308
	(0.0709)	(0.0630)
Age Class, 6-10	0.0470	-0.0244
	(0.0390)	(0.0404)
Age Class, 11+	0.127***	-0.101***
	(0.0339)	(0.0341)
ICT Specialists		0.101***
		(0.0253)
ICT Training for Other Employees		0.0386*
		(0.0216)
Fast Broadband		0.135***
		(0.0235)
Other Digital Technologies		0.0331***
		(0.00917)
Initial Log-Productivity		0.298***
		(0.0199)
Observations	8,392	8,392
Adj. R^2	0.233	0.373
Industry Fixed Effects	Yes	Yes
Geographic Fixed Effects	Yes	Yes

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

Table 5: OLS estimates of regressions using the logarithm of productivity in 2019 as dependent variable and AI use as main explanatory variable, interacted with size class dummies.

determine the applicability of AI technologies to firms in a sector and thus further explain the sources of the links between AI use and productivity. Furthermore, sectoral differences in the level of ICT intensity – and thus in the diffusion of complementary assets – may determine the ability of firms to capture productivity gains of AI. As in for the previous regressions, we report the estimation results with and without the controls for complementary assets and initial productivity.

The relation between AI use and productivity appears heterogeneous across sectors. When complementary assets are not controlled for, the role of AI for productivity is positive and significant in the Manufacturing, Wholesale & Retail, ICT and Professional & Scientific sectors, with highest magnitude in the ICT sector. These findings may be linked to the previously presented sectoral patterns of AI use among different groups of firms. Although the sectoral shares computed in Table 1 are highest in the ICT sector for AI users, buyers and developers, ICT, Professional & Scientific and Wholesale & Retail sectors have the highest shares of

	Model 1 Manuf. & Util.	Model 2 Construction	Model 3 Wholesale & Ret.	Model 4 Transport & Storage	Model 5 Accom. & Food	Model 6 Inf. & Com.	Model 7 Prof. & Scient.	Model 8 Admin. & Real Est.
Sectoral Productivity Regression for AI Users - No Complementary Assets and Initial Productivity								
AI User	0.0965*	-0.0861	0.0776*	-0.0200	-0.0607	0.217**	0.113*	0.150
	(0.0549)	(0.125)	(0.0457)	(0.0748)	(0.0976)	(0.100)	(0.0631)	(0.0993)
Adj. R^2	0.0546	0.0384	0.0554	0.00683	0.0508	0.0919	0.0746	0.0410
Sectoral Productivity Regression for AI Users - With Complementary Assets and Initial Productivity								
AI User	0.0673	-0.0803	0.0664*	-0.0530	-0.150	0.161	0.118*	0.0618
	(0.0548)	(0.123)	(0.0399)	(0.0716)	(0.100)	(0.0990)	(0.0707)	(0.0921)
Initial Log-Productivity	0.386***	0.242***	0.422***	0.302***	0.137***	0.278***	0.239***	0.373***
	(0.0531)	(0.0465)	(0.0456)	(0.0884)	(0.0326)	(0.0531)	(0.0626)	(0.0651)
Adj. R^2	0.293	0.109	0.306	0.158	0.173	0.234	0.246	0.412
Observations	2,293	891	2,119	539	470	623	682	775
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 6: OLS estimates of sector-specific regressions using the logarithm of productivity in 2019 as dependent variable and AI use as main explanatory variable. The regression models without complementary assets only controls for size and age, the ones with complementary assets also include the ICT controls and the initial logarithm of productivity. Estimated coefficients of size, age, ICT specialists, ICT training, Fast Broadband and Number of other technologies have not been reported, but can be found in Tables A.1 and A.2 in the appendix.

AI developers. In some sectors, the relation between AI use and productivity remains significant even after accounting for initial productivity and the role of complementary assets. In particular, in Professional & Scientific and Wholesale & Retail sectors the coefficients remain significant at the 10% level and in the ICT sector the significance level of the AI users coefficient is equal to 10.38%. However, sectoral regressions pool together different groups of AI users, notably buyers and developers, which may experience different links between AI use and productivity.

Expanding on the results from previous regressions and Section 4, we therefore focus on the role of AI use for productivity by disentangling different types of AI users. In particular, we modify Equation 2 to focus separately on AI buyers and AI developers:

$$\text{Log-Productivity}_{i,t+1} = \alpha + \beta_1 \text{AI}^{\text{Type}}_{i,t} + \beta_2 \text{Initial Log-Productivity}_i + \beta_{\mathbf{X}} \mathbf{X}_{i,t} + \epsilon_i \tag{3}$$

where $\text{AI}^{\text{Type}}_{i,t}$ is a dummy variable indicating the type of AI users considered.[23]

When we distinguish between users buying AI from external providers vis-à-vis those developing their own AI, we find heterogeneous results (see Table 7). Although the coefficients remain positive, AI use alone is not significantly associated with productivity in the buyers case. Conversely, the relation between AI use and productivity is significant for developers, also when accounting for initial productivity and complementary assets.This finding complements previous results. In this respect, AI developers also leverage more specialised ICT skills than AI buyers (see the discussion in Section 4), hinting at possible differences among different types of AI users in the knowledge of AI systems, in their absorptive capacity and in the availability (or degree of maturity) of complementary intangible assets, which may induce heterogeneous productivity patterns. Another driver of the positive and significant association of AI with productivity found for AI developers

[23] Similarly to the analysis presented in Section 4, in a first set of models the dummy equals 1 for AI buyers and 0 otherwise, and then it equals 1 for AI developers and 0 otherwise.

Productivity regression for AI Buyers and Developers

	AI buyers		AI developers	
	Model 1	Model 2	Model 3	Model 4
AI Buyer/Developer	0.0449	0.0222	0.125***	0.106**
	(0.0297)	(0.0302)	(0.0481)	(0.0530)
Size Class, 20-49	-0.00173	-0.0321*	-0.00199	-0.0318*
	(0.0178)	(0.0170)	(0.0178)	(0.0170)
Size Class, 50-249	-0.00581	-0.0989***	-0.00747	-0.0986***
	(0.0215)	(0.0224)	(0.0215)	(0.0224)
Size Class, 250+	0.0657*	-0.122***	0.0583*	-0.126***
	(0.0348)	(0.0386)	(0.0351)	(0.0386)
Age Class, 6-10	0.0469	-0.0237	0.0473	-0.0232
	(0.0390)	(0.0404)	(0.0389)	(0.0403)
Age Class, 11+	0.127***	-0.0999***	0.130***	-0.0980***
	(0.0339)	(0.0341)	(0.0338)	(0.0340)
ICT Specialists		0.100***		0.0960***
		(0.0252)		(0.0254)
ICT Training for Other Employees		0.0379*		0.0380*
		(0.0215)		(0.0216)
Fast Broadband		0.136***		0.135***
		(0.0235)		(0.0236)
Other Digital Technologies		0.0337***		0.0326***
		(0.00919)		(0.00917)
Initial Log-Productivity		0.297***		0.297***
		(0.0200)		(0.0200)
Observations	8,392	8,392	8,392	8,392
Adj. R^2	0.232	0.373	0.233	0.373
Industry Fixed Effects	Yes	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes	Yes

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

Table 7: OLS estimates of regressions using the logarithm of productivity in 2019 as dependent variable and AI buyers/developers as main explanatory variables.

may lie in the possibility that AI developers sell AI technologies to buyers. We further discuss these two interpretations in Section 6, where we provide evidence in favour of the first one. Furthermore, although the significant relation between AI development and productivity cannot be interpreted in a causal perspective due to the presence of firm selection into AI use, this issue is likely mitigated by the inclusion of initial productivity as a control variable, which is positive and significant. Similarly to the regressions for all users, size and age become negative and significant when accounting for initial productivity, and complementary assets related to digitalisation remain all positive and significant.

We further test the robustness of the findings presented above by estimating two additional sets of models. The first explores the link between AI use and productivity employing a different specification focused on labour productivity growth rates, and the second changes the productivity proxy used as dependent variable, moving from labour productivity to multi-factor productivity. These robustness checks confirm the absence of a significant AI-productivity link for AI users and buyers, and its existence for developers.[24]

[24]The results estimating labour productivity growth regressions and productivity regressions using multi-factor productivity are discussed in Sections A.2 and A.3 in the appendix.

5.3 The effect of AI on developers' productivity

In this section we develop a different specification aimed at further assessing whether the use of AI developed in-house has a positive effect on productivity, tackling in a different way possible sources of estimation bias. We have indeed already showed that AI is positively associated with productivity in the case of users developing their own AI. However, the OLS estimation may be biased due to the presence of endogeneity in the AI-productivity relation, as AI use is related to self-selection of larger and more productive firms. Despite the AI-productivity link remains significant for developers even after controlling for a series of relevant confounding factors, the existence of omitted variables may still bias our results.

Following Hamilton and Nickerson (2003) and Clougherty et al. (2016), we rely on an endogenous treatment regression model (ET from now on), a latent variable approach that belongs to the family of selection models (see Heckman, 1976, 1978; Maddala, 1983). This choice is consistent with two facts. First, we want to correct for self-selection of firms into AI use (see also Shaver, 1998; King and Tucci, 2002; Campa and Kedia, 2002). Differently from standard IV models (i.e., two-stage least squares, or 2SLS), the ET method corrects for the selection of firms into AI use by estimating a selection and an outcome model. Estimates include the coefficient (ρ), which captures the direction of selection and whether it is significant.[25] Second, the relevant endogenous variable – the use of AI developed in-house – is a dummy variable. The ET method has the advantage of using a Probit-like model in the selection equation. Differently, the first stage of the 2SLS method is based on a linear probability model, whose coefficients can be interpreted as probabilities at the cost of generating predicted values outside of the unity range of the probability space.

In our case, the model is estimated via full information maximum likelihood (FIML henceforth), which allows for a weighted estimation procedure and simultaneously estimates the selection equation (i.e., using the dummy for AI developers as dependent variable) and the outcome equation (i.e., the productivity regression), as described below, by assuming joint normality of errors (ϵ_i, ω_i):[26]

$$\begin{aligned} &\text{Log-Productivity}_{i,2019} = \alpha + \beta_1 \text{AI}^{\text{Dev}}_{i,2018} + \beta_2 \text{ Log-Productivity}_{i,2011} + \beta_{\mathbf{X}} \mathbf{X}_i + \epsilon_i \\ &\text{AI}^{\text{Dev}}_{i,2018} = \begin{cases} 1, & \text{if } \beta_{\mathbf{Z}} \mathbf{Z}_i + \omega_i > 0 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{4}$$

where $\text{AI}^{\text{Dev}}_{i,2018}$ is the endogenous dummy variable for the use of in-house developed AI, $\text{Log-Productivity}_{i,2011}$ is the firm-level productivity in 2011, $\mathbf{X}_{i,2011}$ is a vector of controls including size and age classes in 2011, other controls related to ICT skills (specialists and training), fast broadband and other digital technologies in 2018, as well as industry and geographic fixed effects, and $\mathbf{Z}_i$ includes $\text{Log-Productivity}_{i,2011}$, $\mathbf{X}_i$ and an additional variable W_i, which is excluded from the outcome equation. The significance of the correlation

[25] The sign of ρ accounts for the relation between unobservables affecting outcome variables with unobservables affecting selection.

[26] Conversely, the limited information maximum likelihood (LIML henceforth) estimation approach estimates the model in two steps. The residuals from the first step, where a Probit-like model is estimated, are used to compute the Inverse Mills Ratio, which serves as a control for the selection of firms into AI use in the outcome equation. The coefficient ρ estimated by the FIML procedure is the counterpart of the estimated coefficient of the inverse Mills ratio in the LIML procedure.

between the errors is a test for the presence of selection into treatment, and thus of the endogeneity of the treatment variable. The coefficient of AI developers in the context of the ET model can be interpreted as an average treatment effect. Furthermore, the specification of the outcome equation encompassing the logarithm of productivity, the size and age dummies in 2011 is consistent with the long difference estimation used by related analyses to estimate the effects of digital technology diffusion (see e.g., Acemoglu and Restrepo, 2020; Babina et al., 2021).

Even though not necessary thanks to the joint normality assumption, the ET model provides estimates robust to specification errors when an additional variable W_i is included in the selection equation, but exluded from the outcome equation. This variable needs to comply with two conditions (Puhani, 2000): it must strongly predict the endogenous dummy variable (i.e., be relevant), and has to be exogenous (i.e., satisfy the exclusion restriction), given other controls.[27] We employ the share of ICT workers at the industry SNA38 level in 2011 computed starting from French worker-level data (i.e., DADS) for such purpose.[28] We define as ICT workers the employees classified in the 2003 French PCS classification under the 4-digit classes 388a, 388b, 388c, 388d, 388e, 478a, 478b, 478c, 478d and 544a.[29]

First, concerning the relevance of the industry share of ICT workers in 2011, the results in Section 4 show that AI developers are significantly and positively linked to complementary assets related to the digital transformation, and in particular to ICT human capital. In this respect, the industry share of ICT workers in 2011 is a proxy for the ICT-related human capital pre-existing to the diffusion of AI that is a key factor for the development of AI by firms (see Section 4 and also Harrigan et al., 2021; Babina et al., 2023). Indeed, a higher share of ICT workers in an industry is likely to increase – on average – the absorptive capacity of firms towards new digital technologies by facilitating their assimilation, further development and implementation into production (Cohen and Levinthal, 1989; Griffith et al., 2003).

Second, we correct for two sources of endogeneity possibly affecting the industry share of ICT workers in 2011: the investments in complementary ICT assets following AI adoption and the presence of relations between ICT and productivity. On the one hand, we compute the share of ICT workers in 2011, when AI adoption was very unlikely in France. Therefore, the use of AI by a firm may unlikely have affected French firms and workers in 2011 or in the previous years. On the other hand, we include the productivity of firms in 2011 and the ICT-related complementary assets from previous regressions (i.e., ICT specialists and training for other employees, use of fast broadband, and other digital technologies) in the ET specification. The presence of these controls accounts for possible confounding factors in the relation between the industry share of ICT workers and productivity at the firm level. The productivity of firms in 2011 accounts for possible direct or indirect relations between the industry share of ICT workers in 2011 and firm productivity in 2019. The presence of ICT-related complementary assets in 2018 addresses the potential impact of industries' absorptive capacity in 2011 on both their use of ICTs and productivity, and further controls therefore for possible

[27] As highlighted by Puhani (2000), in practice these are the same conditions that are required by instrumental variables in the 2SLS procedure.

[28] As a consequence, we will use the industry classification in Table 1 for the industry fixed effects.

[29] This classification focuses on ICT intensive occupations and, with the exception of class 544a, is nested in the techies definition used in Harrigan et al. (2021), which includes all occupations in the 2-digit classes 38 (Technical managers and engineers) and 47 (Technicians) of the 2003 French PCS classification. The PCS codes listed above include for instance computer engineers, programmers, developers, database administrators, and IT technicians. Further details and information on the PCS classification can be found here.

ICT-productivity relations beyond AI. Also, the presence of size in the ET specification helps further reduce possible sources of endogeneity to the extent to which ICT investments are more likely in larger firms.

The Effect of AI Development of Productivity

	Model 1 - No ICT Controls			Model 2 - ICT Controls		
	OLS	ET - Outcome	ET - Selection	OLS	ET - Outcome	ET - Selection
AI Developer	0.161***	0.307***		0.117**	0.163*	
	(0.047)	(0.075)		(0.046)	(0.095)	
Size Class, 20-49	0.026	0.024	0.169*	0.011	0.011	0.079
	(0.016)	(0.016)	(0.098)	(0.017)	(0.017)	(0.103)
Size Class, 50-249	0.058***	0.054***	0.401***	0.004	0.003	0.144
	(0.018)	(0.018)	(0.098)	(0.020)	(0.020)	(0.105)
Size Class, 250+	0.105***	0.091***	0.923***	-0.013	-0.016	0.415***
	(0.021)	(0.022)	(0.091)	(0.028)	(0.028)	(0.109)
Age Class, 6-10	-0.066**	-0.064**	-0.249*	-0.063**	-0.062**	-0.213
	(0.029)	(0.029)	(0.134)	(0.028)	(0.028)	(0.138)
Age Class, 11+	-0.063***	-0.059**	-0.388***	-0.055**	-0.054**	-0.333***
	(0.024)	(0.024)	(0.105)	(0.024)	(0.024)	(0.109)
2011 Log-Productivity	0.471***	0.471***	0.021	0.462***	0.462***	-0.012
	(0.027)	(0.027)	(0.067)	(0.027)	(0.027)	(0.058)
ICT Specialists				0.098***	0.096***	0.408***
				(0.024)	(0.024)	(0.109)
ICT Training for Other Employees				0.009	0.009	0.049
				(0.021)	(0.021)	(0.094)
Fast Broadband				0.106***	0.105***	0.211**
				(0.024)	(0.024)	(0.092)
Other Digital Technologies				0.025***	0.025***	0.208***
				(0.009)	(0.009)	(0.050)
2011 Share of ICT Workers			0.092***			0.069***
			(0.025)			(0.024)
Observations	7,422	7,422	7,422	7,422	7,422	7,422
Adj. R^2	0.403			0.411		
ρ		-0.140	-0.140		-0.0453	-0.0453
P-Value$_\rho$		0.00859	0.00859		0.505	0.505
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 8: Productivity regressions in endogenous treatment (ET) models. Rho is the correlation between errors from the first and the second stage, and P-Value indicates the significance of Rho.

We report the estimation results of Equations 4 and the corresponding OLS estimates in Table 8, which presents two types of models: with and without complementary assets. The results of both selection equations are in line with the estimations reported in Table 3 of Section 4: AI developers are larger and younger, and AI development is significantly related to the presence of ICT specialists, the use fast broadband and other digital technologies. Furthermore, the share of ICT workers is positively and significantly associated with AI development independently from the presence of complementary assets, suggesting that the excluded variable W_i is strongly associated with the endogenous treatment. The outcome equation estimates of the ET Model 1 without complementary assets highlight a positive and significant coefficient for AI developers, suggesting a positive causal effect. However, this specification may be biased by the potential presence of relations between the share of ICT workers and productivity other than the one induced by AI. Contrarily, the outcome equation results of the ET Model 2 do not, as complementary assets are controlled for. Despite reducing the strength of the effect, this remains positive and significant, confirming that the in-house development of AI has a positive effect on the productivity of firms.

Finally, the term ρ – whose significance can be interpreted as a test of endogeneity of the treatment – is negative in both specifications, implying that unobservables positively (respectively, negatively) affecting firm productivity tend to occur with unobservables reducing (respectively, increasing) the probability to use AI (e.g., investments crowding out the ones in AI technologies). The term ρ is significantly different from 0 when complementary assets are not included in the specification, but it loses the significance when these are controlled for. This indicates that complementary assets appear *per se* able to rule out the problem of self-selection into AI, suggesting that the estimation reported in previous sections are likely robust to these issues.

6 Discussion and implications

In this section, we further discuss about the implications of our analysis. Focusing on the characteristics of AI users, buyers and developers presented in Section 4, our estimation results highlight that complementary assets – the use of other digital technologies, fast broadband connection and ICT skills – are key for AI use, but that AI users are not all alike. AI developers leverage indeed on more in-depth ICT skills by employing ICT specialists, whereas AI buyers are only weakly significantly linked to ICT training. The existence of differences among different types of AI users are confirmed by the findings uncovered in Section 5. Specifically, our analysis reveals that AI developers are more productive and that the use of AI tools developed in-house has a positive impact on the productivity of developers. Conversely, we do not find evidence of a significant AI-productivity association for AI users overall or for AI buyers, when initial productivity levels and complementary assets are controlled for. The positive association between AI use and the productivity of developers is robust to several estimation techniques and does not seem due to self-selection of those firms into AI use, but rather to the effect of AI on their productivity.

These results may have two possible interpretations. First, productivity gains may be experienced by AI developers because they use AI technologies to improve their productivity (e.g., reduction in operating costs or innovations induced by AI technologies). Second, the AI-productivity relations found for AI developers may be accounted for by the increase in the output experienced by firms upon selling their AI technologies to other firms.

Albeit the two mechanisms are not mutally exclusive, our empirical analysis provides support in favor of the first hypothesis. AI developers rely indeed significantly on more specialised ICT skills and are more likely already endowed with complementary intangible assets, as the ICT and Professional & Scientific sectors exhibit the highest shares of AI developers. They may therefore also have higher absorptive capacity that may help translate AI development into productivity returns. It may indeed take time for the effect of AI on firms' productivity to materialise, also due to the necessity to implement a series of complementary intangible investments (see also Brynjolfsson et al., 2018, 2021). As a consequence, AI technologies may not yet significantly boost productivity for other users. Furthermore, the results of the regressions assessing the

AI-productivity link by sector, presented in Section 5.2, suggest that the productivity gains of AI users are at least partially driven by firms which do not sell AI algorithms as their main (sector of) activity. AI users are found indeed to be more productive also in the Wholesale & Retail and Professional & Scientific sectors. Firms in these sectors may have the possibility to train AI algorithms on large amounts of data, suggesting that AI development may be directly relevant for their core business.

Productivity Regressions by AI Type

	Model 1	Model 2
Only AI Developer	-0.0206	0.0556
	(0.0709)	(0.0667)
Only AI Buyer	0.00131	-0.000960
	(0.0321)	(0.0321)
AI Buyer & Developer	0.141**	0.148*
	(0.0661)	(0.0789)
Size Class, 20-49	-0.0216	-0.0316*
	(0.0182)	(0.0170)
Size Class, 50-249	-0.0823***	-0.0987***
	(0.0240)	(0.0224)
Size Class, 250+	-0.100**	-0.127***
	(0.0415)	(0.0386)
Age Class, 6-10	0.0376	-0.0232
	(0.0384)	(0.0403)
Age Class, 11+	0.123***	-0.0977***
	(0.0333)	(0.0340)
ICT Specialists	0.110***	0.0972***
	(0.0266)	(0.0253)
ICT Training for Other Employees	0.0418*	0.0386*
	(0.0232)	(0.0215)
Fast Broadband	0.158***	0.135***
	(0.0254)	(0.0236)
Other Digital Technologies	0.0403***	0.0325***
	(0.00997)	(0.00917)
Initial Log-Productivity		0.297***
		(0.0200)
Observations	8,392	8,392
Adj. R^2	0.249	0.373
Industry Fixed Effects	Yes	Yes
Geographic Fixed Effects	Yes	Yes

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

Table 9: Productivity regressions employing AI Type as main explanatory variable. Model 1 and 2 use productivity as dependent variable.

Furthermore, we present additional evidence in favour of the first hypothesis by estimating Equation 2 encompassing a categorical variable that groups different types of AI users in mutually exclusive groups (non-user, only AI buyer, only AI developer, and AI buyer & developer) instead of the previously used AI buyer or developer dummies. This regression specification is aimed at further understanding whether the role of AI for the productivity of developers is accounted for by firms that are only developers or by firms both buying and developing AI technologies. This is relevant for interpreting the results from previous Sections 4 and 5. Indeed, firms that are only AI developers are more likely than firms in other AI categories to sell their AI technologies to third parties. Conversely, firms that both buy and develop AI technologies are more likely to use such technologies to reduce operating costs or to improve their processes or products. Accordingly, the estimated results from models employing these mutually exclusive categories may further inform about which interpretation is better supported by the data.[30]

We report the estimated results in Table 9, with Models 1 and 2 reporting the regressions using the logarithm of productivity as dependent variable.[31] In particular, Model 1 includes controls for firm characteristics (size and age) and complementary assets (presence of ICT specialists and training, use of fast broadband and of other digital technologies). Model 2 also controls for firms' initial productivity (see Equation 2). Firms that are only AI buyers do not exhibit a statistically different productivity from the one of non-AI users, in line with previous results. Concerning AI developers, we see that firms that are only AI developers are not significantly more productive than their non-AI counterpart in the reference category, although the relevant coefficient remains positive. In turn, the productivity of firms that both develop and buy AI is significantly higher than other firms, even when the initial levels of productivity are accounted for.[32]

These results provide further support in favor of the evidence that the productivity patterns of AI developers are mostly related to increases in productivity induced by AI technologies, rather than to sales of AI technologies to third parties.[33]

7 Concluding remarks

In this study we focus on the characteristics of French firms using AI technologies and explore the association between AI use and firm productivity. We use detailed survey microdata collected by the French national statistical office, which provide detailed information on technology use in 2018 and are matched with firms' balance sheets containing additional firm-level characteristics over a longer time period, until 2019.

The contribution of this research is threefold. First, it presents several facts regarding the diffusion of AI technologies in France and the characteristics of different types of AI users, notably distinguishing AI buyers from developers. AI buyers tend to be larger than other firms, while AI developers are also younger. The ICT sector exhibits the highest share of AI users, especially developers. Second, the study highlights the role of complementary assets in AI adoption. Measures of firm digitalisation and human capital, such as the use of business digital technologies, digital infrastructure (i.e., fast-broadband connection), and the presence of ICT skills, are positively and significantly related to the use of AI. The distinction between AI buyers and developers also reveals that they hinge on different types of human capital. Third, our work explores the link between AI use and firm productivity. On average, AI use tends to be positively linked with firm productivity.

[30] Regressions using sales as dependent variable may not be as precise as productivity regression specifications using mutually exclusive AI categories to disentangle between the two proposed interpretations. First, higher productivity may also translate in higher sales for AI developers thanks to the increase in their competitiveness. Second, AI technologies can also be used to create innovations (Agrawal et al., 2018; Cockburn et al., 2018), which are likely to induce an increase in sales as well (see also Babina et al., 2021), especially in sectors where the AI-productivity nexus is significant (see Table 6).

[31] The reference category is non-users.

[32] More than half of AI developers also buy AI technologies. Therefore, results in Table 9 are not driven by a minority of firms.

[33] The estimated coefficients of the controls closely resemble those discussed in Section 5.1. First, being larger and older is negatively linked with future productivity when we account for initial productivity and complementary assets. As size and age are linked to these firm characteristics, the results suggest that the productivity of larger/older firms may grow less conditional on initial productivity and ICT intensity. Second, the estimated coefficients indicate a positive link between all complementary assets and productivity.

This pattern seems to originate from large firms and to be more prominent in the ICT sector. However, when considering all AI users together, this link seems to be largely driven by the self-selection into AI use of firms with higher productivity and that already leverage other complementary assets key to realise the returns of digital transformation. In contrast, when focusing on AI developers, who already rely on more specialised ICT skills, the link between AI use and productivity remains positive and significant beyond self-selection and presence of complementary assets, hinting at positive effects of AI on their productivity.

This suggests that AI may not yet significantly boost productivity for all users, and that it may take time for the effect of AI on productivity to emerge. Investments in human capital and intangibles may be necessary before AI fully integrates into the activities of its users (see also Brynjolfsson et al., 2021, 2018). However, the opportunities to fully leverage the potential of AI technologies may not be equally distributed among firms. Indeed, larger and more productive companies turn out to be those more likely to use AI, and this appears relevantly related to their complementary assets. This suggests that in the future productivity gains from the diffusion of AI technologies may be captured by a handful of firms, possibly widening productivity gaps between leaders and other firms (also see Corrado et al., 2021). In this context, policy makers can play a key role to foster an inclusive digital transformation, enabling AI use and its returns to be more widespread across firms and sectors (see Calvino and Criscuolo, 2022; Calvino and Fontanelli, 2023 for further discussion of relevant policy levers).

Although comprehensive in several respects, further research may extend the scope of the current analysis in different directions. First, additional work may focus on further exploring the role of complementary assets for different groups of AI adopters. In particular, linking French matched employer-employee (DADS) data with ICT surveys and balance sheet data at the firm level could allow exploring in further detail the role of human capital for AI adoption and its productivity returns. Second, future analysis may also explore the role of management and organisational structure for AI adoption and its returns, which are additional relevant complementary factors for which limited information was available in the current data sources. Third, future work could focus on other outcomes beyond firm productivity, such as employment and wages, to further asses the extent to which productivity effects of AI are related to labour market dynamics.

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A Appendix

A.1 Regression tables

Sectoral Productivity Regression for AI Users without Complementary Assets and Initial Productivity

	Model 1 Manuf. & Util.	Model 2 Construction	Model 3 Wholesale & Ret.	Model 4 Transport & Storage	Model 5 Accom. & Food	Model 6 Inf. & Com.	Model 7 Prof. & Scient.	Model 8 Admin. & Real Est.
AI User	0.0965*	-0.0861	0.0776*	-0.0200	-0.0607	0.217**	0.113*	0.150
	(0.0549)	(0.125)	(0.0457)	(0.0748)	(0.0976)	(0.100)	(0.0631)	(0.0993)
Size classification (baseline) = 1, 20-49	0.0805**	0.0615	-0.0241	-0.0749	-0.0218	0.0551	0.0338	-0.166*
	(0.0364)	(0.0377)	(0.0357)	(0.0770)	(0.0538)	(0.0932)	(0.0603)	(0.0858)
Size classification (baseline) = 2, 50-249	0.158***	0.0596	0.00798	-0.0985	-0.119	-0.117	-0.154*	-0.140
	(0.0402)	(0.0445)	(0.0377)	(0.0740)	(0.101)	(0.112)	(0.0811)	(0.0985)
Size classification (baseline) = 3, 250+	0.352***	0.110**	0.0570	0.105	-0.174	0.0345	-0.133	-0.248
	(0.0467)	(0.0522)	(0.0444)	(0.0989)	(0.207)	(0.111)	(0.0865)	(0.167)
Age classification = 1, 6-10	-0.0237	-0.0428	-0.0952	-0.0545	0.185***	0.480	0.100	0.0232
	(0.0746)	(0.0771)	(0.0828)	(0.131)	(0.0699)	(0.291)	(0.135)	(0.186)
Age classification = 2, 11+	0.178***	-0.0437	-0.00552	0.0508	0.198***	0.607**	0.156	0.344**
	(0.0633)	(0.0671)	(0.0671)	(0.126)	(0.0693)	(0.274)	(0.125)	(0.169)
Observations	2,293	891	2,119	539	470	623	682	775
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0546	0.0384	0.0554	0.00683	0.0508	0.0919	0.0746	0.0410

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

Table A.1: OLS estimates of sector-specific regressions using the logarithm of productivity in 2019 as dependent variable and AI use as main explanatory variable.

Sectoral Productivity Regression for AI Users with Complementary Assets and Initial Productivity

	Model 1 Manuf. & Util.	Model 2 Construction	Model 3 Wholesale & Ret.	Model 4 Transport & Storage	Model 5 Accom. & Food	Model 6 Inf. & Com.	Model 7 Prof. & Scient.	Model 8 Admin. & Real Est.
AI User	0.0673	-0.0803	0.0664*	-0.0530	-0.150	0.161	0.118*	0.0618
	(0.0548)	(0.123)	(0.0399)	(0.0716)	(0.100)	(0.0990)	(0.0707)	(0.0921)
Size classification (baseline) = 1, 20-49	-0.0110	0.0418	-0.0479	-0.0372	-0.0377	-0.0122	0.0216	-0.177**
	(0.0333)	(0.0377)	(0.0320)	(0.0663)	(0.0514)	(0.0896)	(0.0544)	(0.0697)
Size classification (baseline) = 2, 50-249	-0.0641	0.0314	-0.0414	-0.114	-0.196*	-0.274**	-0.0928	-0.359***
	(0.0430)	(0.0522)	(0.0349)	(0.0737)	(0.102)	(0.120)	(0.0768)	(0.0908)
Size classification (baseline) = 3, 250+	-0.0249	0.0668	-0.0330	-0.103	-0.429**	-0.173	-0.0986	-0.674***
	(0.0559)	(0.0730)	(0.0479)	(0.120)	(0.192)	(0.109)	(0.0965)	(0.165)
Age classification = 1, 6-10	-0.0773	-0.136	-0.00932	-0.0249	0.0825	0.355	0.0341	-0.0929
	(0.0912)	(0.0837)	(0.0776)	(0.161)	(0.0652)	(0.302)	(0.159)	(0.158)
Age classification = 2, 11+	-0.120*	-0.231***	-0.124**	-0.115	0.00908	0.303	-0.0533	-0.0901
	(0.0719)	(0.0700)	(0.0621)	(0.139)	(0.0656)	(0.288)	(0.145)	(0.145)
ICT Specialists	0.117**	-0.0245	0.0489	0.311*	0.0976	0.138	-0.103	0.433***
	(0.0500)	(0.0902)	(0.0412)	(0.164)	(0.0775)	(0.0976)	(0.0658)	(0.107)
ICT Training for Other Employees	0.0758**	-0.000168	-0.0302	-0.0617	0.170*	0.140	0.0929	0.0877
	(0.0358)	(0.0889)	(0.0328)	(0.0817)	(0.0935)	(0.0906)	(0.0605)	(0.0717)
Fast Broadband (>= 100 Mbits/sec)	0.108**	0.00831	0.167***	0.0525	0.303***	0.0306	0.142**	0.365***
	(0.0461)	(0.0577)	(0.0431)	(0.0721)	(0.0837)	(0.0911)	(0.0599)	(0.111)
Initial Log-Productivity	0.386***	0.242***	0.422***	0.302***	0.137***	0.278***	0.239***	0.373***
	(0.0531)	(0.0465)	(0.0456)	(0.0884)	(0.0326)	(0.0531)	(0.0626)	(0.0651)
Other Digital Technologies	0.0711***	0.0159	-0.000527	0.0130	0.0514*	0.0528	-0.0575**	0.104***
	(0.0176)	(0.0254)	(0.0165)	(0.0342)	(0.0265)	(0.0534)	(0.0284)	(0.0371)
Observations	2,293	891	2,119	539	470	623	682	775
R-squared	0.301	0.132	0.313	0.194	0.213	0.263	0.271	0.429
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.293	0.109	0.306	0.158	0.173	0.234	0.246	0.412

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

Table A.2: OLS estimates of sector-specific regressions using the logarithm of productivity in 2019 as dependent variable, AI use as main explanatory variable, and complementary assets and initial productivity as controls.

A.2 Estimation results from productivity growth regressions

In this section we further assess the firm-level association between AI use and productivity focusing on productivity growth rates computed over different time horizons. We compute labour productivity growth as the logarithmic difference between productivity in a base year (2015, 2016, 2017, 2018) and 2019. This is relevant, because returns to AI adoption are related to intangible investments which may take time to be implemented by firms, possibly creating J-curve dynamics (Bryniolfsson et al., 2021, see also Babina et al., 2021).

We estimate the following productivity growth regression:

$$\text{Productivity Growth}_{i,\tau,2019} = \alpha + \beta_1 \text{AI}^{\text{Type}}_{i,t} + \beta_2 \text{Initial Log-Productivity}_i + \beta_{\mathbf{X}} \mathbf{X}_{i,\tau} + \epsilon_i \tag{A.1}$$

Where Productivity Growth$_{i,\tau,2019}$ is the productivity growth rate computed over the period τ, 2019, where τ is equal to either 2015, 2016, 2017 or 2018 and other regressors and controls are the same as the ones of specification 2.[34]

The productivity growth regressions, whose results are reported in Table A.3, further suggest that the relation between AI adoption and productivity growth rates depends on the type of AI users considered. AI developers grow significantly more than other firms when the time horizon on which growth is computed is longer than one year. Conversely, the overall AI use variable, as well as the one indicating the use of AI technologies bought from third parties, are either negative or very close to 0, and not significantly linked with productivity growth in the time periods considered.

These findings confirm the evidence emerging from the productivity regressions discussed in Section 5.2: in the current phase, AI adoption might not have a significant immediate impact on productivity for all users. This could be attributed to the time required for the productivity-enhancing effects of AI to emerge (see also Brynjolfsson et al., 2021, 2018). In contrast, AI developers likely already possess the specialised ICT skills that complement AI (see Section 4).

[34]Productivity growth rates are computed as the log-difference between the productivity in 2019 and in τ. Controls also include the past (i.e., $\min(\text{Year of birth; 2011})$) log-productivity level as a proxy for the initial level of productivity, likely exogenous to AI use. To some extent, this variable may capture also dynamics of catch up towards the frontier.

Growth Regressions for AI Users, Buyers and Developers

	AI Users				AI Buyers				AI Developers			
	2018-2019	2017-2019	2016-2019	2015-2019	2018-2019	2017-2019	2016-2019	2015-2019	2018-2019	2017-2019	2016-2019	2015-2019
AI user	0.00805	0.00178	-0.0153	-0.00471	0.00322	0.00336	-0.0221	-0.0121	0.0447	0.0908**	0.0815**	0.0903**
	(0.0139)	(0.0231)	(0.0232)	(0.0260)	(0.0144)	(0.0250)	(0.0250)	(0.0277)	(0.0281)	(0.0372)	(0.0365)	(0.0396)
Size class 1, 20-49	0.00781	0.0358***	-0.0186	0.0663***	0.00776	0.0358***	-0.0187	0.0662***	0.00793	0.0358***	-0.0181	0.0658***
	(0.00913)	(0.0120)	(0.0131)	(0.0166)	(0.00913)	(0.0120)	(0.0131)	(0.0166)	(0.00912)	(0.0120)	(0.0131)	(0.0166)
Size class 2, 50-249	0.00733	0.0328**	-0.0208	0.130***	0.00723	0.0329**	-0.0210	0.129***	0.00742	0.0326**	-0.0211	0.130***
	(0.0112)	(0.0143)	(0.0145)	(0.0201)	(0.0112)	(0.0143)	(0.0145)	(0.0201)	(0.0112)	(0.0144)	(0.0146)	(0.0201)
Size class 3, 250+	0.00892	0.00485	-0.0667***	0.119***	0.00907	0.00484	-0.0667***	0.119***	0.00745	0.000722	-0.0706***	0.114***
	(0.0149)	(0.0190)	(0.0191)	(0.0247)	(0.0149)	(0.0189)	(0.0191)	(0.0247)	(0.0150)	(0.0191)	(0.0191)	(0.0245)
Age classification = 1,	0.00817	-0.0222	-0.0461	-0.0771**	0.00808	-0.0222	-0.0461	-0.0770**	0.00833	-0.0224	-0.0467	-0.0764**
	(0.0213)	(0.0281)	(0.0321)	(0.0328)	(0.0213)	(0.0281)	(0.0321)	(0.0328)	(0.0213)	(0.0281)	(0.0322)	(0.0328)
Age classification = 2,	0.00892	-0.0322	-0.0459*	-0.0569**	0.00872	-0.0322	-0.0457*	-0.0569**	0.00964	-0.0304	-0.0445*	-0.0552**
	(0.0180)	(0.0221)	(0.0240)	(0.0277)	(0.0179)	(0.0222)	(0.0240)	(0.0277)	(0.0180)	(0.0221)	(0.0240)	(0.0277)
ICT Specialists	-0.00989	0.0122	0.00332	0.000655	-0.00957	0.0122	0.00296	0.000565	-0.0114	0.00871	-0.000549	-0.00253
	(0.0135)	(0.0177)	(0.0184)	(0.0214)	(0.0136)	(0.0176)	(0.0183)	(0.0214)	(0.0136)	(0.0175)	(0.0183)	(0.0214)
ICT Training for Other Employees	-0.00212	-0.0101	0.00859	0.0101	-0.00194	-0.0101	0.00860	0.0103	-0.00207	-0.0105	0.00762	0.00937
	(0.0107)	(0.0188)	(0.0187)	(0.0212)	(0.0106)	(0.0188)	(0.0187)	(0.0212)	(0.0106)	(0.0190)	(0.0189)	(0.0214)
Fast Broadband (>= 100 Mbits/sec)	-0.00378	0.0122	0.0243	0.0319	-0.00358	0.0122	0.0243	0.0320	-0.00424	0.0106	0.0221	0.0299
	(0.0120)	(0.0192)	(0.0183)	(0.0220)	(0.0119)	(0.0192)	(0.0183)	(0.0220)	(0.0120)	(0.0191)	(0.0183)	(0.0220)
Other Digital Technologies	-0.00281	-0.00231	0.00654	-0.00230	-0.00267	-0.00234	0.00660	-0.00220	-0.00324	-0.00342	0.00524	-0.00363
	(0.00514)	(0.00633)	(0.00732)	(0.00800)	(0.00515)	(0.00632)	(0.00731)	(0.00798)	(0.00512)	(0.00634)	(0.00735)	(0.00801)
Initial Log-Productivity	-0.00512	-0.00390	-0.0380**	-0.112***	-0.00517	-0.00392	-0.0379**	-0.112***	-0.00487	-0.00355	-0.0373**	-0.112***
	(0.00611)	(0.0137)	(0.0155)	(0.0325)	(0.00610)	(0.0137)	(0.0155)	(0.0325)	(0.00611)	(0.0137)	(0.0155)	(0.0325)
Observations	8,344	8,275	8,229	7,979	8,344	8,275	8,229	7,979	8,344	8,275	8,229	7,979
Adj. R^2	0.00735	0.00819	0.0169	0.0544	0.00728	0.00820	0.0170	0.0544	0.00796	0.00977	0.0179	0.0553
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A.3: Regression results estimating growth rates computed over different time horizons as a function of AI Users, AI Buyers and AI Developers and other controls.

A.3 Testing an alternative productivity measure: multi-factor productivity

Productivity Regressions Using Multi-factor Productivity

	MFP in 2019		
	AI Users	AI Buyers	AI Developers
	Model 1	Model 2	Model 3
AI User/Buyer/Developer	0.0175	0.00386	0.128***
	(0.0256)	(0.0273)	(0.0423)
Size Class, 20-49	0.243***	0.243***	0.244***
	(0.0177)	(0.0177)	(0.0177)
Size Class, 50-249	0.433***	0.433***	0.433***
	(0.0251)	(0.0251)	(0.0251)
Size Class, 250+	0.823***	0.823***	0.818***
	(0.0433)	(0.0433)	(0.0433)
Age Class, 6-10	0.0508	0.0505	0.0526
	(0.0374)	(0.0374)	(0.0372)
Age Class, 11+	-0.0945***	-0.0951***	-0.0911***
	(0.0324)	(0.0324)	(0.0322)
ICT Specialists	0.0535**	0.0542**	0.0493**
	(0.0240)	(0.0240)	(0.0239)
ICT Training for Other Employees	0.0373*	0.0378*	0.0376*
	(0.0208)	(0.0208)	(0.0210)
Fast Broadband	0.148***	0.148***	0.146***
	(0.0229)	(0.0229)	(0.0229)
Other Digital Technologies	0.0260***	0.0263***	0.0247***
	(0.00856)	(0.00855)	(0.00858)
Initial Log-Productivity (MFP)	0.418***	0.418***	0.419***
	(0.0210)	(0.0210)	(0.0210)
Observations	8,329	8,329	8,329
Adj. R^2	0.576	0.576	0.577
Industry Fixed Effects	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes

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

Table A.4: Productivity regressions employing multi-factor productivity as the dependent variable.

In this section we run a robustness check on the results of the Sections 5.1, 5.2 and A.2 by employing multi-factor productivity (MFP) as dependent variable in the estimation of the regressions 2 and A.1. The estimation results confirm the findings from the previous sections, suggesting that the AI-productivity link found above does not depend on the type of productivity proxy employed for the analysis.

Firm-level MFP has been computed at the 2-digit industry level via the procedure of Wooldridge (2009) for the population of French firms between 2008 and 2019. Indeed, a production function cannot be consistently estimated by employing the 2018 data only – corresponding to our matched ICT-balance sheet data –, as the GMM procedure suggested by Wooldridge (2009) to tackle endogeneity in firms' characteristics requires a panel dataset.

We report the results in Table A.4. More specifically, we report the estimation results for Equation 2 employing productivity in 2019 as the dependent variable. These two specifications are estimated for AI users, buyers and developers separately. Similarly to the results for labour productivity, the relation between MFP and AI use is positive and significant for AI developers only. AI users and buyers are positively linked to the MFP, but their coefficients are not significantly different from 0. Finally, further unreported analysis suggests that AI developers' MFP grows significantly more, also when complementary factors and initial productivities are taken into account, differently from AI users and buyers, confirming the results discussed in Sections 5 and A.2.