The human capital of firms using AI

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Abstract

We exploit a uniquely comprehensive combination of data sources to better understand the level of complementarity between human capital and AI in French firms. We show that highly specialised technical occupations, notably ICT R&D engineers and ICT managers, play a key role for firms using AI. We show important difference between firms developing their own AI systems (AI developers) and firms buying AI from external providers (AI buyers). The former leverage on a broader set of higher level intellectual occupations with respect to the latter, including ICT, non-ICT and non-technical higher intellectual occupations. AI-human capital relations are also heterogeneous across economic sectors, with ICT occupations being more relevant in services while non-ICT technical occupations in manufacturing.

Keywords: Artificial intelligence, human capital, technological diffusion.

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1 Introduction

Understanding the links between human capital and Artificial intelligence (AI) is a crucial research question given the ground-breaking potential of AI for diverse applications in several sectors (Agrawal et al., 2022) and its ability to spur innovation across the economy (Cockburn et al., 2018; Bianchini et al., 2022). On the one hand, human capital is a key asset for technology adoption (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005; Harrigan et al., 2021), particularly for what concerns advanced technologies such as AI (Goos and Savona, 2024). On the other hand, the rapid diffusion of AI will change the demand for skills (Alekseeva et al., 2021; Borgonovi et al., 2023) and reshape labour markets due to a large exposure of occupations to AI (Felten et al., 2021; Eloundou et al., 2023). Yet, evidence on the links between human capital and AI use is limited and mostly focused on the United States (Babina et al., 2023; Alekseeva et al., 2021), particularly as the diffusion of AI technologies among firms remains low (Calvino and Fontanelli, 2023b; Acemoglu et al., 2022).

We leverage a unique combination of data sources from the 2018 official ICT survey, linked employer-employee data (LEED), balance-sheets, and the business registry between 2011 and 2018 to study the human capital structure of a representative sample of French firms. Specifically, we use information on detailed occupations, based on the 2003 version of the French classification of occupations *Professions et catégories socioprofessionnelles* (PCS 2003) to explore the role of four macro categories of human capital in firms using AI: higher intellectual, intermediate, clerical and manual occupations. Higher intellectual occupations are characterised by highly specialised technical knowledge or managerial capabilities requiring in-depth scientific, administrative and commercial knowledge. Intermediate occupations include non-administrative technicians and workers positioned between executives and execution agents. Clerical occupations encompass commercial and administrative execution agents, as well as personnel providing direct services to individuals and requiring manual tasks. Finally, manual occupations are performed by qualified or unqualified workmen. We then dive on the role of technical occupations, which overlap with both higher intellectual (i.e., engineers) and intermediate occupations (i.e., technicians) by investigating the role of highly granular information and communication technology (ICT) and non-ICT technical occupations, exploring the distinction between engineers and technicians, as well as the role of the different specialisations of ICT engineers (e.g., ICT engineers specialised in R&D). Next, we explore the differences in the human capital structure of firms buying AI from external providers (AI buyers) from those developing their own AI systems (AI developers). This is highly relevant in order to distinguish the characteristics of firms relying on the implementation of AI systems developed externally from those playing an active role in integrating AI in their business operations, also considering their different returns to AI use (Calvino and Fontanelli, 2023a). Lastly, we investigate the role of human capital for AI use across different sectors.

Our analysis highlights that human capital is tightly linked with the use of AI among firms. The presence of higher intellectual occupations is significantly and positively associated with the use of AI. Among these occupations, ICT engineers appear to play a particularly important role. The further disaggregation of ICT engineers at the most granular level available reveals that those specialised in R&D and ICT managers drive the AI-human capital link. This suggests a prominent role of R&D capabilities for firms using AI, as well as the need of specialised coordinators to deploy AI systems within firms. Furthermore, AI developers leverage R&D capabilities to a larger extent than AI buyers, indicating that higher innovative capabilities are required to implement in-house developed AI systems. Nonetheless, ICT engineers specialised in R&D are also significantly linked to ones bought externally. Importantly, we show that AI developers leverage several different types of ICT human capital, differently from AI buyers. The significant presence of ICT engineers specialised in computer networks and telecommunications suggests that AI development also requires an internal physical digital infrastructures to manage data flows. AI developers also leverage ICT managers, indicating higher requirements of coordination of the workflow of different ICT occupations by specialised managers. The significant presence of ICT engineers specialised in sales in AI developers suggests that these firms may sell AI solutions to other firms. Third, AI buyers leverage more the presence of other digital technologies, with larger coefficients for CRM and a significant use of ERP software. Furthermore, AI buyers significantly rely on fast broadband connection – differently from AI developers –, suggesting strong complementarities with the use of external digital infrastructures (e.g., cloud services) for using their AI tools. Fourth, the internal development of AI systems characterises firms with a broader set of non-ICT higher professional occupations in technical and non-technical domains. This suggests that the presence of ICT knowledge is not enough for AI development, and that in-depth scientific, commercial and administrative knowledge is highly complementary to the development of AI systems. At the same time, AI developers are characterised by lower shares of workers in clerical occupations. This relation may be due to an automation effect of AI towards workers mainly performing routine tasks. Overall, these findings reveal that AI buyers rely on simpler implementations and use of AI technologies in their organisation vis-à-vis developers. Finally, firms in different sectors are characterised by significant differences in terms of inputs, outputs and production operations. The domain of applicability of AI systems to production may change accordingly, determining shifts in the human capital needed to accommodate their use. In almost all of the service sectors considered, ICT occupations appear more relevant for firms using AI. ICT engineers are key in service sectors characterised by higher availability of data, higher ICT and R&D intensity, whereas higher shares of ICT technicians characterise other services. Instead, AI users in the manufacturing sector leverages more non-ICT technicians. This difference in the link between AI and human capital likely reflects sectoral specificities. Indeed, services are generally more data intensive and AI can be more easily integrated into production as software for predictive analysis. Conversely, in manufacturing AI systems are more likely to be predominantly embedded into physical machines or tools.

We expand the existing literature along three dimensions. First, we exploit novel and uniquely comprehensive data outside the United States to characterise the human capital of AI users. We assess the role of human capital based on official sources for France and leveraging a detailed classification of occupations, that enables us to distinguish the level and type of human capital relative to the population of workers employed by the representative sample of firms considered. Conversely, existing contributions leverage proxies of human capital such as skills and the educational attainments of workers/job-postings, mostly in the U.S. (see e.g. Babina et al., 2023). Second, we assess the role of human capital for different AI users, i.e. buyers and developers. This is considerably important due to the role played by those groups of users, with the former firms likely leveraging simpler implementation of AI and the latter firms relying on internal expertise and knowledge, also extending beyond the ICT domain, to build cutting-edge AI systems. Furthermore, the differences in human capital across AI buyers and developers may be at the basis of their different productivity returns to AI use (Calvino and Fontanelli, 2023a). Third, we explore the sectoral heterogeneity of the link between AI and human capital. Such a distinction sheds light on which human capital is necessary to deploy different AI systems across sectors, possibly further informing the discussions around the changes in labour markets brought by AI.

Overall, our findings indicate a strong complementarity between human capital and the use of AI, and highlight relevant heterogeneity in the patterns of AI use among different types of users and sectors. This is not only critical for the design of policies aimed at coping with changes in occupation and skill demand associated with AI, but also for firms that aim at leveraging the potential of the digital transformation in the age of AI.

The remaining of the paper is organised as follows. Section 2 analyses the existing evidence about the links between AI use and the workforce. Section 3 focuses in detail on the sources of data used for the analysis and reports key summary statistics. Section 4 describes the econometric framework applied in sections 5 and 6, which present the main results of the analysis. Section 7 summarises the key findings and discusses possible avenues for future research.

2 Existing evidence on AI and workforce

In this section we review the literature on the intersection of AI and labor markets. Although human capital appears a key factor needed to leverage the potential of AI (Borgonovi et al., 2023; Calvino and Fontanelli, 2023b), the empirical literature on the relation between them is still limited. This is due to challenges in gathering data measuring at the same time the use of AI by firms and their human capital. The existing literature has consequently pursued two distinct approaches. On the one hand, a set of studies leverage online job postings data to estimate firm-level demand for AI skills and AI-related investments, relying on Lightcast (formerly Burning Glass) data. On the other hand, analyses of the labor market's exposure to AI technologies employ the tasks and occupations classification provided by the O*NET database.

First, we start by discussing the contributions using Lighcast data. A key contribution to this stream of literature is the work by Babina et al. (2023), that explore whether AI investments are associated with changes in labour composition and workforce organisation. They match data leveraging a unique combination of sources that capture both the stock of current employees – provided by Cognism Inc, which offers job histories and educational attainment for individuals – and the demand for new employees – from job postings data provided by Lightcast – among US firm. They show that AI investments – based on the presence of employees with AI-related skills – are associated with firms becoming flatter in their organisational structure, a general upskilling trend (i.e., increase in the share of workers with at least college education), and a higher demand for educated workers in technical fields (i.e., STEM degrees, data analysis and IT).

Taking a different perspective, several contributions focus instead on the demand of AI-related jobs, as measured by the presence of AI-related skills in job postings, often in the US market. Many of these works are based on based on Lightcast (former Burning Glass) data (Squicciarini and Nachtigall, 2021; Borgonovi et al., 2023; Alekseeva et al., 2021; Acemoglu et al., 2022). Squicciarini and Nachtigall (2021) study the demand for AI-related jobs by companies in five countries (Canada, Singapore, the United Kingdom, and the United States) from 2012 to 2018. Both the number of online vacancies requiring AI-related skills and the number of AI-related skills per job posting across all the examined countries increased in the period considered. Service sectors show the highest demand for AI skills, especially ICT, financial/insurance, and consulting services sectors. Borgonovi et al. (2023) shows that AI-related online job postings grew by 33% between 2019 and 2022 in a set of 14 countries. Large differences exists across countries and the US is leading the increase in the demand for AI in the countries considered, in line with the dynamics of AI-related patents (see e.g., Deperi et al., 2023). Moreover, a limited number of occupations require the skills specialised in the development, adaptation, and modification of AI systems. Less than 1% of all job postings search for candidates with AI skills. Furthermore, despite the most demanded skills in AI vacancies relate to machine learning, firms demand workers specialised in AI characterised by a broad skill mix, including technical as well as socio-emotional skills. Similarly, Alekseeva et al. (2021) builds a measure for the firm-level demand of AI workers. Between 2010 and 2019, AI demand rapidly increased, in line with the aforementioned evidence of Squicciarini and Nachtigall (2021). Furthermore, they investigate which skills are demanded by firms, and focus on the firm-level characteristics predicting AI demand by them. Firm size, cash holdings and R&D investments are significantly and positively related to AI skills. Moreover, the study reveals that AI skills are sought by firms offering higher wages and providing larger wage premium, in particular in Information Technology (IT) professionals and managerial occupations.

Notwithstanding the increase in the demand for AI-related skills in online job postings, the effects of AI technologies on labour markets may yet have to materialise. Using job posting data from Lightcast, Acemoglu et al. (2022) find that AI exposure of establishments is associated with lower hirings, but does not find an association between AI diffusion and the dynamics of employment and wages at the sector and occupation level.[1]

Second, several works estimate the exposure to AI of occupations relying on the tasks and occupation information provided by O*NET database. Brynjolfsson et al. (2018) estimate the exposure to machine learning of tasks in occupations from the O*NET dataset. They show that the majority of occupations in most sectors have at least some tasks related to machine learning, but that only few of them are characterised by tasks exposed to machine learning. Savona et al. (2022) reviews the literature on the role of automation technologies for the labour market and finds that firms in service sectors are more exposed to data-intensive technologies than in Manufacturing sector. Felten et al. (2021) build a measure of AI exposure by linking the information on AI-related skills from the Electronic Frontier Foundation AI Progress Measurement with O*NET occupations. Webb et al. (2018) estimate the occupational exposure to AI by leveraging the patent-level information about what a technology does and O*NET descriptions about tasks to build an AI exposure measure. The two measures of AI exposure proposed by (Felten et al., 2021) and (Webb et al., 2018) are different. The former depends on occupations' tasks overlapping to what AI can do, whereas the latter builds upon the amount of AI-related patenting activities concerning tasks in specific occupations. However, both studies arrive at the same conclusion, showing that high skilled occupations are more exposed to AI.

These measures of occupational exposure are used by Acemoglu et al. (2022) to study whether the AI-exposed occupations and industries between 2010 and 2018, and Albanesi et al. (2023) to explore the effect of AI

[1]Using investments spikes to measure automation shocks (also see Jin and McElheran, 2018; Aghion et al., 2020; Domini et al., 2021, 2022), the firm-level analysis of Bisio et al. (2023) suggests however a positive effect of automation technologies shocks (including ones in AI, among the others) on the employment of Italian firms between 2011 and 2019. Similarly, no evidence of technological unemployment from digital technologies adoption by Italian firms is instead found by Ughi and Mina (2023).

on the dynamics of sectoral employment of 16 European countries between 2011 and 2019. The former study find no significant impact on the employment level of AI-exposed occupations and industries. Consistently with existing evidence on skill biased technological change (Autor et al., 2003), the latter study finds that employment shares are positively related to their AI exposure, specially among skilled professions with higher shares of young workers.

Finally, the recent wave of generative AI models has been object of several contributions. Eloundou et al. (2023) estimates the exposure of occupations from O*NET to Large Language Models (LLM) in the US labour market using human experts and GPT-4 itself to classify tasks as exposed to AI. The analysis finds that the use of LLM will likely have an impact on the large majority of the US workforce, with higher wage jobs more exposed to them. Furthermore, the productivity of workers will likely increase, as found by other contributions (see also Brynjolfsson et al., 2023; Noy and Zhang, 2023; Peng et al., 2023; Eloundou et al., 2023; Kreitmeir and Raschky, 2023). However, the impact of generative AI on occupations hinges on the overlap in the tasks performed by workers and AI systems (Dell'Acqua et al., 2023).

In this study we consider a novel database for the analysis of AI and labour markets. We match official data sources on the use of digital technologies by French firms and the population of their workers, that jointly provide information on AI use and workers' occupations. A similar approach has been undertaken by Calvino and Fontanelli (2023b) and Calvino and Fontanelli (2023a), that study the characteristics of AI users leveraging ICT surveys and find that they significantly rely of ICT human capital.[2] However, ICT surveys alone only provide information on the broad presence of ICT skills. Conversely, the database used in this work also encompasses granular information on the occupations of workers employed by a firm, beyond the ones leveraging tasks related to the ICT domain. This gives us the opportunity to comprehensively explore the workforce of a representative set of AI users and provide an analysis on the relation between AI and human capital. This work is indeed the first contribution to comprehensively characterise the workforce of a representative sample of firms using AI, thereby offering key insights on the role of human capital for AI users.

3 Data

In this section, we discuss the data employed in the analysis and present key summary statistics. We use four data sources relative to the year 2018: French ICT surveys, LEED, balance sheet data and the business register. These sources are matched together relying on a unique firm identifier (the *Siren* code).

Our analysis relies on microdata obtained from the 2019 French ICT survey, known as the "Enquête sur les Technologies de l'Information et de la Communication (TIC)." [3] Administered by INSEE, the French statistical office, this survey features a rotating sample of approximately 9000 firms operating in the manufacturing, utilities,construction and non-financial market services sectors, with specific questions related to the use of

[2]Calvino and Fontanelli (2023b) shows the importance of ICT-related human capital for AI users, that are significantly linked with the presence of both ICT specialists among employees and ICT training for non-ICT employees firms in several of the countries under consideration. Calvino and Fontanelli (2023a) finds that AI users are not all alike. AI developers significantly leverage ICT specialists, whereas AI buyer rely on ICT training. This suggests that different uses of AI may not have the same level of requirements in terms of ICT knowledge.

[3]Additional details about the survey can be accessed here.

advanced digital technologies in the year 2018.[4] The sample is designed to be representative of firms with a workforce of 10 or more persons employed and is exhaustive for those with more than 500 employees. These data offer an unprecedented level of granularity and representativeness in comparison to other commercial surveys. This unique quality allows an in-depth examination of AI adoption dynamics among the population of French firms with 10 or more persons employed.

Part of the ICT survey is indeed dedicated to questions on AI use by firms. In particular, firms are asked whether they used AI technologies in 2018, a year preceding the recent boom in generative AI.[5] Our primary AI use variable is thus binary, taking the form of a dummy variable that indicates whether a firm used AI technologies in 2018. Importantly, the data provide a meaningful categorisation of AI users into two distinct groups: AI buyers and AI developers. AI buyers refer to firms using AI technologies bought from external providers, while AI developers are firms employing AI systems developed in-house.

Moreover, the survey includes questions about the broadband connection speed, that we use as an indicator of digital infrastructure. Specifically, we construct a binary variable to denote the presence of a fast broadband connection. This variable takes value of 1 when the speed equals or exceeds 100 megabits per second, that represents the highest speed among the available choices in the question addressing broadband connection speed. Finally, the ICT survey incorporates questions regarding the adoption of other business digital technologies or tools, encompassing the use of Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) software, and participation in e-commerce activities. These technologies serve as indicators for the existence of an internal digital infrastructure within firms, enabling them to collect data on both the outcomes and the inputs of business operations. Notably, business digital technologies like CRM, ERP, and e-commerce activities exhibit a lower likelihood of being linked to sector-specific attributes when contrasted with other advanced technologies, such as robots and 3D printers, which may be considerably contingent on the sector.

The second source of information employed in our analysis is the LEED obtained from the *Déclaration annuelle de données sociales* (hereafter referred to as DADS). This dataset provides comprehensive insights into the French workforce. We use employee-level information on hours worked and occupation type. We aggregate this data at the firm level by computing various statistics related to the full-time equivalent (FTE henceforth) of workers in occupation classes. These elaborations are at the basis of the shares of workers in occupation classes that we use throughout this work. Each share is defined as the total number of FTE in an occupation class over the total number of workers in the firm. Shares therefore range between 0 and 1.

We consider the following occupation classes based on the 2003 PCS classification:[6]

- Higher intellectual occupations (PCS 3)
- Intermediate occupations (PCS 4)
- Clerical occupations (PCS 5)

[4] It is important to note that the questions pertaining to advanced digital technologies vary on an annual basis.

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

[6] For additional details on the PCS 2003 classification, please refer to this link. The occupation is hierarchically structured. For instance, 4-digit classes starting with 3 (e.g., 3888a) belongs to the PCS aggregate class 3.

- Manual occupations (PCS 6)

These considered occupation classes broadly reflect the level and type of workers' human capital.[7] The class PCS 3 includes occupations requiring highly specialised technical knowledge, such as engineers and technical executives, along with employees performing managerial functions that demand in-depth scientific, administrative or commercial knowledge. The tasks performed by the workers belonging to this class are typically difficult to routinise, and are also the ones mostly exposed to AI according to the literature (see e.g., Felten et al., 2021). The class PCS 4 encompasses intermediate positions, between executives and execution agents (e.g., supervisors and foremen), and non-administrative technicians (e.g., appliance repairer, laboratory technicians). Occupations in class PCS 5 are based on routine tasks that do not require specialised knowledge and do not involve physical work. This class includes commercial workers (e.g., cashiers and salesmen), administrative employees (e.g., secretaries, employees in accounting offices) and personnel providing direct services to individuals which may involve manual tasks (e.g., receptionists and waiters). Finally, the class PCS 6 includes both qualified (e.g., control room operator, quality control agent, truck drivers) and unqualified (e.g., press operators, sawmill worker) workmen.

We then explore the role of technical occupations (techies), defining them as the group of engineers and technicians within a firm, following the definition by Harrigan et al. (2021, 2023). The first two digits of the PCS 2003 classification allow us to identify the classes of engineers (PCS 38) and technicians (PCS 47), which belong to higher intellectual occupations (PCS 3) and intermediate occupations (PCS 4), respectively. Among technical occupations, we distinguish ones specialised in ICT and non-ICT tasks. To identify ICT occupations, we rely on the four digits of the occupational classes defined by the 2003 PCS classification.[8] ICT workers are classified under classes 388a, 388b, 388c, 388d, 388e, 478a, 478b, 478c, and 478d, where 388* classes refer to ICT engineers and 478* classes to ICT technicians. In the regression analysis, we will also consider the single classes of ICT engineers 388a, 388b, 388c, 388d, 388e, that respectively corresponds to ICT engineers specialised in R&D activities, ones supervising administration and support operations, ICT managers, engineers responsible for commercial relations with clients and ones specialised in network computing and telecommunications. We further discuss the type of occupations characterising workers in these classes in the Appendix C.

Lastly, we match the ICT survey with firm-level administrative data, specifically from FICUS, FARE (including firm's balance sheets), and the business register, providing information on the stocks of establishments per firm.[9] Using these datasets, we calculate various firm-level statistics, encompassing physical and intangible capital, age, and whether a firm exports. We use the measures of capital to build two indexes of capital intensity. The first, the PIK ratio, is the logarithmic difference between the physical and intangible capital, whereas the second, the PKL ratio, between the physical capital and the total amount of FTE workers in the firm. All variables have been adjusted using sector-specific deflators provided by the Banque de France, with the exception of intangible capital, that has been deflated using ones by the EUKLEMS & INTANProd database

[7]We exclude workers belonging to the class PCS 2, including craftsmen, merchants, and business owners, for consistency. However, the main results are robust to the inclusion of the class PCS 2 into the analysis.

[8]For further details and information on the PCS classification, refer to this link. Note that the classification has been modified in 2003 and 2019.

[9]For additional details about these datasets, please refer to this link, this link, and this link, respectively.

(Bontadini et al., 2023). We distinguish multi-plant firms based on information in the business register, which associates plants (*Siret* codes) with firms (*Siren* codes).

3.1 Summary statistics

Summary Statistics

	All	Other Firms	AI Users
AI Users	11.49%	0%	1%
AI Developers	3.21%	0%	27.93%
AI Buyers	9.99%	0%	86.9%
Sales	17893.14	13710.96	50094.17
Age	24.09	24.14	23.71
PIK Ratio	4.56	4.59	4.39
PKL ratio	2.51	2.53	2.36
Physical Capital	6738.26	4853.26	21368.61
Multi-plant	30.39%	29.9%	34.14%
Exporter	30.7%	30.15%	34.91%
Fast Broadband	13.16%	12.07%	21.55%
CRM	27.83%	25.95%	42.29%
ERP	48.12%	46.93%	57.26%
E-Commerce	14.1%	13.71%	17.11%
Share Higher Intellectual Occupations (PCS 3)	15.05%	14.04%	22.82%
Share Intermediate Occupations (PCS 4)	16.02%	15.94%	16.66%
Share Clerical Occupations (PCS 5)	28.95%	28.85%	29.72%
Share Manual Occupations (PCS 6)	39.84%	41.02%	30.8%
Share Non-Technical Higher Intellectual Occupations (PCS 3 Excl. 38)	8.73%	8.34%	11.69%
Share Non-Technical Intermediate Occupations (PCS 4 Excl. 47)	10.83%	10.8%	11.06%
Share Technical Workers (PCS 38 and 47)	11.52%	10.84%	16.73%
Share Engineers (PCS 38)	6.32%	5.7%	11.12%
Share Technicians (PCS 47)	5.2%	5.14%	5.6%
Share Non-ICT Engineers (PCS 38 Excluding ICT)	4.08%	4.03%	4.43%
Share Non-ICT Technicians (PCS 47 Excluding ICT)	4.19%	4.22%	4.03%
Share ICT Engineers (ICT of PCS 38)	2.24%	1.66%	6.7%
Share ICT Technicians (ICT of PCS 47)	1%	0.93%	1.57%
Share ICT Engineers R&D (PCS 388a)	1.14%	0.8%	3.82%
Share ICT Engineers Admin. & Support (PCS 388b)	0.22%	0.19%	0.48%
Share ICT Engineers Manager (PCS 388c)	0.62%	0.49%	1.66%
Share ICT Engineers Sales (PCS 388d)	0.2%	0.15%	0.58%
Share ICT Engineers Telecom. (PCS 388e)	0.06%	0.04%	0.15%

Table 1: Weighted averages for the whole sample and distinguishing between AI users and other firms. Results for AI users, buyers and developers, exporter, multi-plant, fast broadband, CRM, ERP, E-commerce and occupation shares are in percentage terms.

In this section, we discuss a series of summary statistics related to French AI users and reported in Table 1. The averages are computed for the entire sample, distinguishing between firms that used AI in 2018 and those that did not. Observations are weighted using the sampling weights provided by the ICT survey, ensuring that the statistics are representative of the population of French firms with 10 or more persons employed.

In France in 2018, firms using AI are a minority, accounting for 11.49% of total firms in our sample. Distinguishing between different types of AI users, the descriptive statistics highlight that 9.99% of firms purchased AI from external sources, while only 3.21% developed their AI in-house. These figures suggest that some firms both bought and developed AI concurrently, and the presence of a potential relationship between the decisions to buy and develop AI. This may also imply that firms may choose to leverage external AI capabilities even if they are capable of developing AI in-house, or that firms may leverage AI acquired from external providers to build their own AI systems. Notably, 53.1% of AI developers are also buyers, while only 8.56% of non-developers are also buyers. Additionally, 17.07% of AI buyers are also developers, whereas only 1.67% of non-buyers are also developers. These statistics suggest that the decisions to buy and develop AI technologies are positively related.

AI users are on average larger and younger than non-users, in line with existing evidence (Acemoglu et al., 2022; Zolas et al., 2020). This underscores the relevance of complementarities, as firms of larger size are more likely characterised by availability or presence of complementary assets (Calvino and Fontanelli, 2023b). Similarly, AI users tend to be more intensive in intangible capital and labor than non-users, providing further preliminary indications of the role of complementarities and suggesting their embedding in the intangible capital and workforce of firms. AI users are also characterised by larger amounts of physical capital, a relation which may however depend on size. Additionally, AI users are more likely to be exporters and multi-establishment firms. This aligns with the idea that selling in larger, more complex, and diversified markets incentivises firms to adopt AI technologies. Indeed, these firms may have more data at their disposal, which are crucial for carrying out predictive AI analyses.

Regarding the digital status of firms, AI users leverage fast broadband services and adopt business digital technologies more frequently than other firms. The presence of fast broadband is indeed a necessary condition for the use of digital technologies that may be highly complementary to AI, such as cloud computing. Similarly to export and multi-plant status, firms employing these technologies may already have a well-established digital infrastructure, enabling them to collect and organise data. In this respect, the diffusion of AI may depend on the existing digital infrastructure of firms, whether external or within the firm, as suggested by various studies (Calvino and Fontanelli, 2023b; McElheran et al., 2023).

Focusing on the shares of workers, summary statistics reveal that AI users tend to have a significantly higher share of workers in higher intellectual occupations and a lower one of manual workers. The shares of workers in intermediate and clerical occupations are only slightly larger in AI users. This pattern may be influenced by the sectoral composition of the sample, which includes Manufacturing and Construction firms that are less likely to adopt AI technologies compared to firms in non-financial market services. When workers specialised in technical occupations are excluded from the computation, the difference in the workers' share of higher intellectual occupations is still notable, and keep being relatively smaller for intermediate occupations. Examining technical occupations, it is evident that AI users rely on much higher intellectual occupations, especially in the ICT domain. Finally, when ICT engineers are disaggregated in different occupations, the highest share is found among ICT engineers specialised in R&D. This suggests that firms adopting AI may need to invest in R&D.

The summary statistics discussed in this section suggest that, on average, AI users are larger, younger, more intangible and labor intensive, more digitalised, and rely more on higher intellectual occupations, particularly in the ICT domain. However, these firm characteristics may be correlated among each other, and possibly influenced by a number of confounding factors that are not taken into account in a simple descriptive analysis. For this reason, we delve into the relationship between AI and these firm characteristics through the econometric models presented in the next section.

4 Methods

In this section, we present the empirical models employed in our study. We use two types of models, namely a probit and a biprobit, depending on the dependent variable under analysis. In particular, as discussed in the next paragraphs, we focus on either overall AI use, or we distinguish AI buyers and developers.

First, when the dependent variable is AI use, we estimate the following probit model:

$$\text{Pr}(\text{AI User}_i) = \Phi(\text{Share}_i, \text{Firm Characteristics}_i, \text{Digital Controls}_i, \text{Industry}_i, \text{Region}_i) \tag{1}$$

where AI User$_i$ is the dummy variable indicating the use of AI by firm i in 2018. The main explanatory variable (or vector of variables) is Share$_i$, which is our proxy for human capital and includes the within-firm share of one or more occupation classes, based on the PCS 2003 classification. Firm Characteristics$_i$ consists of variables measuring key firm characteristics, while Digital Controls$_i$ are dummy variables gauging the level of digitalisation of the firm. Additionally, Industry$_i$ and Region$_i$ represent industry and regional fixed effects.

Second, when distinguishing between AI buyers and developers, we estimate the following biprobit model:

$$\text{AI Buyer}_i = \begin{cases} 1 & \text{if } \beta_1 X_i + \varepsilon_{i,1} > 0, \\ 0 & \text{otherwise,} \end{cases}, \ \text{AI Developer}_i = \begin{cases} 1 & \text{if } \beta_2 X_i + \varepsilon_{i,2} > 0, \\ 0 & \text{otherwise,} \end{cases}, \ \textbf{Corr}(\varepsilon_{i,1};\ \varepsilon_{i,2}) = \rho \tag{2}$$

Here, X_i is a vector of firm-level characteristics, which includes the same covariates as Equation 1 (i.e., Share$_i$, Firm Characteristics$_i$, Digital Controls$_i$, Industry$_i$, Region$_i$). This model captures unobservable factors influencing joint decisions related to dependent binary outcomes. The biprobit model enables therefore to control for the correlation between the decisions to buy and develop in-house AI systems by modeling the correlation between the error terms of the single models. In our case, it is relevant to control for such unobservables because the different AI decisions considered seem to be positively correlated (see the discussion in Section 3.1).

We introduce a set of covariates to control for potential confounding factors in the relationship between AI use and human capital, as measured by the different occupation shares. Firm Characteristics$_i$ include the logarithms of firm sales and age, the PIK ratio (log of physical to intangible capital ratio), the PKL ratio (log of physical capital to total FTE workers), logarithm of physical capital, as well as export and multi-plant status dummies. Since AI users tend to be larger and younger, accounting for these characteristics is relevant when exploring the role of complementary assets such as human capital (Calvino and Fontanelli, 2023b). The capital structure of the firm is likewise relevant for AI adoption, as AI can be perceived as a combination of different tangible and intangible capital components (Corrado et al., 2021). Some of these characteristics might be captured by occupation shares, given that complementary assets are inherently correlated with each other.

Likewise, multi-plant and export status dummies capture the presence of multiple markets, with the multi-plant variable also capturing, to some extent, whether a firm is involved in the production of several goods or the provision of multiple services. A larger market size or the presence of multiple sources of data related to different activities might increase their incentive to invest in AI technologies.

Digital Controls$_i$ is a vector of dummies describing the digital characteristics of firms and encompassing the presence of fast broadband and the use of business digital technologies (CRM, ERP, e-commerce). The former variable captures the quality of the digital infrastructure, while the latter reflects the presence of a digital architecture within firms. Both factors are pivotal for the adoption of AI technologies (Calvino and Fontanelli, 2023b; McElheran et al., 2023).

On the one hand, an efficient broadband connection enables firms to leverage the potential of various digital technologies, particularly cloud computing, which is crucial for the use of AI. On the other hand, for the effective use of AI, especially predictive AI, it is essential to leverage meaningful datasets. The presence of business digital technologies plays a crucial role in this context. The use of CRM software and e-commerce practises may be at the basis of the collection of customer and product information, while ERP may indicate the availability of data on productive inputs that can be leveraged to enhance resource efficiency through AI algorithms.

Lastly, we incorporate a set of aggregate industry and regional fixed effects.[10] The aggregate industry dummies capture the average characteristics of firms within industries, thereby controlling the AI-occupation relationship for, among other things, the presence of ICT or data-intensive sectors.[11] Meanwhile, the regional dummy controls for the presence of geographic factors, such as the existence of AI hubs across France (e.g., Paris, Lyon, Nice, and Grenoble areas).

When estimating Equations 1 and 2, we weight observations using the sample weights provided by the French ICT survey. The results discussed in next sections are therefore representative of the population of French firms with more than 10 employees.

5 Which occupations are linked to AI use?

In this section, we present and discuss the results of our analysis concerning the human capital of AI users. We begin by examining the relationship between AI use and aggregate occupation classes in Table 2. Next, we explore the role of technical occupations in Table 3.

We present the estimated margins for Equation 1 in Table 2. For each aggregate class, we run two models: one including the share of workers, as well as the logarithm of sales and age of firms, industry and region fixed effects, and the other also incorporating firm characteristics and digital dummies as additional control variables.

The results highlight that the only occupation class significantly correlated with AI use is the one linked to higher intellectual occupations (see the coefficient of *Share* in Models 1 and 2). The positive coefficient suggests that the presence of a highly specialised workforce is significantly associated with the probability to use AI, also after accounting for other relevant confounding factors (see Model 2). Conversely, other occupation classes tend to have negative coefficients, but they are not statistically significant.

AI users tend to be larger and younger than other firms. However, these characteristics appear to be related to other firm-level variables. The logarithm of sales becomes indeed non significant when comple-

[10]The industry-level regressions in Section 6.2 only include regional dummies.

[11]The industry dummies include categories for Accommodation & Food, Administrative, Real Estate, Construction, ICT, Manufacturing, Utilities, Professional & Scientific, Transportation & Storage, and Wholesale & Retail sectors, broadly corresponding to NACE macro sectors.

AI Users and Occupations

	Higher Intellectual Occupations		Intermediate Occupations		Clerical Occupations		Manual Occupations	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Share	0.0784***	0.0579**	-0.0172	-0.0252	-0.0126	-0.00938	-0.0191	-0.00447
	(0.0238)	(0.0246)	(0.0236)	(0.0239)	(0.0195)	(0.0197)	(0.0190)	(0.0193)
Log Sales	0.00908***	-0.00448	0.0125***	-0.00112	0.0120***	-0.00182	0.0117***	-0.00192
	(0.00307)	(0.00685)	(0.00295)	(0.00676)	(0.00297)	(0.00678)	(0.00297)	(0.00683)
Log Age	-0.0112*	-0.0117*	-0.0125*	-0.0127*	-0.0126*	-0.0128*	-0.0123*	-0.0127*
	(0.00643)	(0.00670)	(0.00644)	(0.00669)	(0.00644)	(0.00668)	(0.00645)	(0.00670)
PIK Ratio		-0.00345		-0.00389		-0.00378		-0.00379
		(0.00420)		(0.00419)		(0.00420)		(0.00421)
PKL ratio		-0.00646		-0.00464		-0.00486		-0.00509
		(0.00754)		(0.00747)		(0.00748)		(0.00752)
Log Physical Capital		0.00888		0.00673		0.00715		0.00743
		(0.00774)		(0.00771)		(0.00771)		(0.00778)
Multi-plant		0.00163		0.000557		0.000686		0.000201
		(0.00977)		(0.00979)		(0.00979)		(0.00981)
Exporter		0.00353		0.00756		0.00695		0.00769
		(0.0108)		(0.0106)		(0.0106)		(0.0106)
Fast Broadband		0.0275**		0.0312***		0.0305**		0.0306**
		(0.0120)		(0.0120)		(0.0120)		(0.0120)
CRM		0.0399***		0.0421***		0.0418***		0.0414***
		(0.00988)		(0.00986)		(0.00984)		(0.00984)
ERP		0.0194*		0.0213**		0.0206**		0.0209**
		(0.0102)		(0.0103)		(0.0102)		(0.0102)
E-Commerce		0.00858		0.00616		0.00754		0.00604
		(0.0124)		(0.0124)		(0.0125)		(0.0125)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.033	.044	.031	.043	.031	.042	.031	.042

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

Table 2: Estimated margins for Equation 1, with the main explanatory variables being share of aggregate PCS classes. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

mentary assets and firm-level controls are accounted for. These results suggest that size is intertwined with complementary assets associated with the level of digitalisation of firms (also see Calvino and Fontanelli, 2023b). The log of firm age is only weakly significant.[12]

AI users are, on average, more intangible intensive, but the relation is not significant. This suggests that AI users leverage on a larger amount of intangible capital than non-users, in line with the idea that AI technologies leverage on higher amounts of complementary intangible assets (Brynjolfsson et al., 2021). Furthermore, in line with the summary statistics discussed in Section 3.1, AI users appear less labor intensive than non-users, even though the PKL ratio does not significantly affect the probability of using AI. Similarly, the relations between AI use and the remaining controls related to firm characteristics are not significant.

[12]However, age is not significantly linked to AI use when technical and ICT workers are considered (see Table A.1). Therefore, age may incorporate the relation between AI and new managerial human capital related to technical and ICT knowledge.

Additionally, our results encompass factors related to the digital infrastructure of firms, which tend to have positive and significant coefficients, indicating a pivotal role of digital infrastructure and other digital technologies in AI use. Specifically, the presence of fast broadband tends to be highly significant across regressions, emphasising its crucial role for AI use. Among business technologies, CRM has the largest and most significant coefficient. Conversely, the presence of ERP is generally weakly significant, and e-commerce is not significant. This suggests that AI may be more related to the output than to the inputs of production.

Overall, the estimation results of Table 2 highlight the relevance of higher intellectual occupations, but that these are not the only complementary assets that matters for AI users. Digital infrastructure is also crucial for AI, enabling the use of other digital technologies closely related to it. However, not all digital assets are equally relevant for AI use. On the one hand, digital infrastructure is crucial as it enables the use of technologies closely related to AI. On the other hand, business technologies are relevant, but not all, as e-commerce does not seem to be significantly related to AI use.

Taking a complementary perspective, we further discuss the results of Equation 1 focusing on the role of techies, i.e., when the workers' shares concern technical occupations. We estimate models based on four different families of occupation classes, with each model consisting of a nested version of the previous one.

We first disaggregate technical occupations (PCS 38 and 47) from their respective aggregate PCS classes (PCS 3 and PCS 4), and add a control for the remaining share of workers in higher intellectual and intermediate occupations (Models 1 and 2). The share of workers in technical occupations is positively relatd to AI use but loses significance when additional complementary assets are included in the regression, suggesting that technical occupations are also correlated with digital assets and other firm characteristics.

Next, we disaggregate technical occupations into engineers (PCS 38) and technicians (PCS 47) in Models 3 and 4. This distinction reveals that the overall share of workers in technical occupations is not significant because the shares of engineers and technicians have opposite relationships with the probability to use AI, respectively positive and negative. However, only the share of engineers is significantly related to AI use, even when additional complementary assets are controlled for. This indicates that the positive coefficient associated with the share of higher intellectual occupations found in Table 2 is likely driven by engineers. Conversely, and confirming previous results found in Table 2, intermediate occupations are not related to AI use.

In Models 5 and 6 of Table 3, we further disaggregate engineers and technicians into ICT and non-ICT classes. Once again, the additional disaggregation uncovers relevant insights regarding the complementary occupations that enable firms to use AI. The share of ICT engineers has a positive and significant coefficient, whereas ICT technicians exhibit a negative but not significant coefficient. This suggests that AI use require the presence of workers specialised in ICT occupations, but specifically, they benefit from the in-depth capabilities offered by ICT engineers.

Lastly, in Models 7 and 8 of Table 3, we explore the link between AI use and the presence of ICT engineers at the 4-digit level of the PCS classification, providing the most detailed occupation classes. These classes encompass very specific occupations related to various ICT-related human capital.[13] We find that ICT engineers specialised in R&D tasks drive the relationship between AI and engineers found in Models 5 and 6 of

[13]We describe these classes in Section C of the Appendix.

AI Users and Technical Occupations

	Technical Occupations		Eng. & Technicians		ICT Eng. & ICT Technicians		Disaggregate ICT Engineers	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.0397	0.0109	0.0442	0.0171	0.0505	0.0218	0.0513	0.0229
	(0.0317)	(0.0329)	(0.0317)	(0.0329)	(0.0319)	(0.0331)	(0.0319)	(0.0331)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	0.00454	-0.00348	0.00791	0.000260	0.00919	0.00198	0.00911	0.00180
	(0.0294)	(0.0301)	(0.0292)	(0.0299)	(0.0289)	(0.0296)	(0.0289)	(0.0296)
Share Technical Occupations (PCS 38 and 47)	0.0490**	0.0302						
	(0.0231)	(0.0235)						
Share Engineers (PCS 38)			0.109***	0.0886***				
			(0.0292)	(0.0297)				
Share Technicians (PCS 47)			-0.0293	-0.0445				
			(0.0377)	(0.0382)				
Share Non-ICT Engineers (PCS 38 excl. ICT)					0.0132	-0.00777	0.0146	-0.00620
					(0.0427)	(0.0430)	(0.0427)	(0.0429)
Share Non-ICT Technicians (PCS 47 Excl. ICT)					-0.0119	-0.0179	-0.0127	-0.0186
					(0.0421)	(0.0428)	(0.0421)	(0.0429)
Share ICT Engineers (ICT of PCS 38)					0.192***	0.170***		
					(0.0388)	(0.0394)		
Share ICT Technicians (ICT of PCS 47)					-0.00517	-0.0481	-0.00122	-0.0426
					(0.0740)	(0.0743)	(0.0741)	(0.0741)
Share ICT Engineers R&D (PCS 388a)							0.204***	0.186***
							(0.0480)	(0.0484)
Share ICT Engineers Admin. & Support (PCS 388b)							0.0860	0.0139
							(0.164)	(0.166)
Share ICT Engineers Manager (PCS 388c)							0.157**	0.146*
							(0.0800)	(0.0803)
Share ICT Engineers Sales (PCS 388d)							0.292**	0.229
							(0.148)	(0.145)
Share ICT Engineers Telecom. (PCS 388e)							0.194	0.219
							(0.176)	(0.171)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	.032	.043	.034	.045	.037	.048	.037	.048

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

Table 3: Estimated margins for Equation 1, with the main explanatory variables being shares of workers in technical occupations. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees. Size and age are included in Models 1, 3, 5 and 7 as additional controls, whereas Models 2, 4, 6 and 8 also include PIK ratio, PKL ratio, physical capital, fast broadband, CRM, ERP, e-commerce. The estimation results for these additional controls are excluded from this table but are available in Table A.1 in Appendix A.

the same table. The coefficient only slightly decreases when additional complementary assets are included. In Model 7, without additional controls, ICT managers and ICT engineers specialised in commercial and technical relations with customers are also significant. However, in Model 8, the coefficient of the latter loses its significance, suggesting that the presence of ICT engineers specialised in sales was possibly capturing the presence of other digital technologies.

Results from Models 7 and 8 confirm that AI users rely on highly specialised ICT occupations. In particular, they reveal two facets of AI. First, they reveal that R&D capabilities are critical for AI use, suggesting that the use of AI is associated with relevant innovation efforts by firms. This evidence is consistent with the findings of (Alekseeva et al., 2021), who shows correlation between AI use and R&D investments. Second, they point to the complex nature of AI technologies, whose use involves both technological and organisational changes (Agrawal et al., 2022). In this context, our results suggests that the deployment of AI in firms may be more easily accomplished by relying on specialised coordinators (i.e., ICT managers).

Finally, we show that the relationships uncovered by the results in Tables 2 and 2 is also present in a period when AI diffusion in France likely had not yet begun. We report in Tables B.1 in Appendix B the estimation results of Equation B.1 when using shares and firm characteristics are computed in 2011, a year in which AI use was very unlikely. The results confirm that higher intellectual occupations are strongly linked to the use of AI by firms and suggest that specific ICT capabilities have likely enabled the adoption of AI by firms.[14] In addition, when studying granular ICT occupations in 2011 and 2018, it is evident that the relevance of ICT engineers specialised in R&D tasks increased with the diffusion of AI technologies, suggesting that the use of AI is tightly linked with innovation capabilities.

The results in this section highlight that the use of AI is significantly related to human capital, and in particular point to a significant link between the presence of workers in higher intellectual occupations and the firm-level probability to use AI. These findings are suggestive of the existence of complementarities in the relation between AI and human capital, in particular the one linked to in-depth ICT knowledge and specialised in R&D activities. This confirms the role of complementarities for AI use to unfold (Brynjolfsson et al., 2021), with a key role of human capital and, more in general, of digital capabilities (see also Santarelli et al., 2022). Our evidence appears in line with the predictions of theories of skill-biased technological change to the extent that occupation shares capture the skills of the workforce (Autor et al., 2003, 1998; Machin and Reenen, 1998). Also, it suggests that the findings of the literature showing that high-skilled workers are more exposed to AI (e.g., Webb, 2020; Felten et al., 2021) are capturing complementary characteristics with high-skilled workers more than the substitutability of AI with respect to them.

6 Heterogeneity in the link between human capital and AI

In this section we explore additional dimensions that may affect the relation between AI use and human capital. First, in Section 6.1 we investigate the extent to which the relation between AI use and human capital depends on the type of AI user considered, in particular distinguishing between AI buyers and AI developers. This builds upon previous empirical evidence that has revealed that these firms may be profoundly different (Calvino and Fontanelli, 2023a). Second, in Section 6.2 we inquire about the existence of sectoral idiosyncrasies in the relation between AI and human capital. AI users may indeed leverage different types of human capital to implement AI systems across sectors.

6.1 AI buyers and AI developers

In this section, we investigate the link between human capital and AI use distinguishing firms that acquire AI systems from external providers from those that develop AI systems internally. We accomplish this by

[14] Furthermore, unreported evidence shows that results are broadly consistent with ones reported when excluding the ICT sector or ICT services (i.e., NACE 62-63).

estimating Equation 2 and presenting results in Tables 4 and 5. In the former we report the link between different types of AI use and aggregate occupation shares, in the latter we focus more closely on the role of technical and ICT occupations.

AI Buyers, AI Developers and Occupations

	Higher Intellectual Occupations Model 1		Intermediate Occupations Model 2		Clerical Occupations Model 3		Manual Occupations Model 4	
	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer
Share	0.00596	0.0514***	-0.0212	-0.00651	0.00742	-0.0225**	0.00263	-0.0153
	(0.0237)	(0.0106)	(0.0228)	(0.0111)	(0.0187)	(0.00956)	(0.0182)	(0.0118)
Log Sales	-0.00111	-0.00174	-0.000282	0.000972	-0.000657	0.000323	-0.000641	0.000433
	(0.00649)	(0.00308)	(0.00633)	(0.00316)	(0.00637)	(0.00314)	(0.00639)	(0.00321)
Log Age	-0.00644	-0.0115***	-0.00637	-0.0130***	-0.00650	-0.0128***	-0.00651	-0.0130***
	(0.00647)	(0.00300)	(0.00646)	(0.00300)	(0.00646)	(0.00296)	(0.00646)	(0.00303)
PIK Ratio	-0.00399	-0.00165	-0.00411	-0.00161	-0.00409	-0.00149	-0.00404	-0.00160
	(0.00399)	(0.00184)	(0.00397)	(0.00187)	(0.00397)	(0.00186)	(0.00398)	(0.00189)
PKL ratio	0.00255	-0.00710*	0.00304	-0.00608	0.00276	-0.00611	0.00290	-0.00643*
	(0.00702)	(0.00370)	(0.00693)	(0.00380)	(0.00694)	(0.00381)	(0.00697)	(0.00382)
Log Physical Capital	0.00125	0.00818**	0.000566	0.00656*	0.00102	0.00676*	0.000858	0.00706*
	(0.00724)	(0.00370)	(0.00715)	(0.00384)	(0.00715)	(0.00385)	(0.00720)	(0.00387)
Multi-plant	-0.00241	0.00728	-0.00229	0.00558	-0.00282	0.00656	-0.00245	0.00545
	(0.00934)	(0.00455)	(0.00936)	(0.00463)	(0.00934)	(0.00462)	(0.00938)	(0.00462)
Exporter	0.000268	0.000337	0.000612	0.00504	0.00134	0.00310	0.000641	0.00516
	(0.0103)	(0.00497)	(0.0102)	(0.00496)	(0.0102)	(0.00487)	(0.0101)	(0.00495)
Fast Broadband	0.0264**	0.00716	0.0268**	0.0105**	0.0267**	0.00969*	0.0266**	0.00973*
	(0.0114)	(0.00520)	(0.0114)	(0.00523)	(0.0114)	(0.00531)	(0.0115)	(0.00512)
CRM	0.0304***	0.0242***	0.0309***	0.0267***	0.0305***	0.0264***	0.0307***	0.0258***
	(0.00951)	(0.00475)	(0.00950)	(0.00488)	(0.00947)	(0.00484)	(0.00946)	(0.00491)
ERP	0.0182*	0.00206	0.0185*	0.00373	0.0185*	0.00294	0.0182*	0.00355
	(0.00975)	(0.00468)	(0.00980)	(0.00473)	(0.00977)	(0.00474)	(0.00979)	(0.00471)
E-Commerce	0.00447	0.00635	0.00414	0.00342	0.00337	0.00627	0.00452	0.00256
	(0.0119)	(0.00536)	(0.0119)	(0.00535)	(0.0120)	(0.00541)	(0.0120)	(0.00530)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Estimated margins for Equation 2, with the main explanatory variables being share of aggregate PCS classes. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

First, the findings reveal that AI users significantly differ in their workforce composition (see Table 4). While AI buyers do not seem to significantly leverage a particular type of human capital, the presence of workers in higher intellectual occupations is significantly and positively linked to the development of AI (see Model 1). Additionally, AI developers employ fewer clerks on average (see Model 3). These results suggest that the workforce composition of AI users depends on the type of AI use considered, with the development of AI systems potentially requiring relatively higher amounts of higher intellectual occupations and lower ones of routinised work. These increases may possibly lead to changes in the overall workforce composition of AI developers.

AI users also exhibit differences in terms of firm characteristics. Similar to the results in Section 5, AI developers and buyers are not significantly larger than other firms. However, AI developers are younger, suggesting the possible presence of innovative AI start-ups driving the development of AI systems (also see Calvino and Fontanelli, 2023b).

Similarly, the digital profile of AI users also differs across buyers and developers. On one hand, the presence of fast broadband is positively and significantly linked to both AI buyers and developers, but in the latter the relation is weaker and becomes not significant when we control for the share of workers in higher intellectual occupations (see Model 1).[15] This indicates that the presence of a complementary digital infrastructure, represented by fast broadband in our specification, is key for firms buying AI from external sources, as they may run their AI models on external platforms thanks to cloud technologies. Conversely, the in-house development of AI systems may not necessarily need the presence of a fast broadband due to the possible internal availability of data and servers.[16] On the other hand, all AI users are significantly linked to CRM software and none to e-commerce activities, while only buyers to ERP software. This suggests the presence of relevant synergies between AI machines and the availability of customer-related data, indicating a potential key role of AI in firms' marketing strategies. The significance of ERP software is likely related to integration of AI tools into these systems to provide predictions based on multiple data sources of firms and assist therefore managerial decision-making.

Second, we present the estimated relationships between AI buyers/developers and technical/ICT occupations reported in Table 5. In line with results presented in the previous section, AI users exhibit different characteristics according to their type. Overall, AI developers significantly rely on higher intellectual occupations even when technical occupations are excluded from the share of workers in the PCS 3 class. This suggests a predominant role of high-level commercial and administrative human capital in these firms. Furthermore, the relationship between AI and technical occupations is positive and significant for AI developers only (see Model 1), indicating the need for general technical knowledge when AI are developed vis-á-vis bought.

In Model 2, we explore the link between different types of AI users and the presence of workers specialised in technical occupation, disaggregating them by their level of human capital, higher in engineers than in technicians. We observe that AI developers are positively and significantly linked to advanced technical human capital only, whereas the relations for AI buyers are not significant.

Further disaggregations of technical occupations into those specialised in ICT and non-ICT domain are explored by Model 3. The significant presence of engineers among AI developers revealed by Model 2 is driven by both ICT and non-ICT advanced knowledge, as represented by the significant and positive coefficients estimated for the shares of both ICT and non-ICT engineers. Conversely, both ICT and non-ICT technicians are not significant, even though non-ICT technicians are very close to the 10% significance threshold (the p-value is 12.2%). Furthermore, AI buyers are significantly and positively linked to specialised ICT engineers only. Other relations are not significant for them.

This, together with the significant presence of workers specialised in non-technical higher intellectual occupations in AI developers, suggests two facts about AI use by firms. First, both the use and development

[15] Similarly, when technical occupations are accounted for, fast broadband is not significantly linked to AI developers (see Tables A.2).

[16] As discussed in (Jin and McElheran, 2018), cybersecurity issues may arise when entrusting proprietary data to external companies, suggesting that the use of AI on cloud platforms may also have cons for companies.

AI Buyers, AI Developers and Technical Occupations

	Technical Occupations Model 1		Eng. & Technicians Model 2		ICT Eng. & ICT Technicians Model 3		Disaggregate ICT Engineers Model 4	
	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	-0.00735	0.0305**	-0.00491	0.0337**	-0.00156	0.0348**	-0.00109	0.0351**
	(0.0306)	(0.0144)	(0.0306)	(0.0145)	(0.0309)	(0.0144)	(0.0309)	(0.0144)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.00599	-0.00125	-0.00448	0.000913	-0.00307	0.00156	-0.00348	0.00170
	(0.0283)	(0.0153)	(0.0283)	(0.0150)	(0.0282)	(0.0148)	(0.0281)	(0.0147)
Share Technical Occupations (PCS 38 and 47)	-0.0177	0.0496***						
	(0.0236)	(0.00982)						
Share Engineers (PCS 38)			0.00776	0.0687***				
			(0.0292)	(0.0122)				
Share Technicians (PCS 47)			-0.0488	0.0193				
			(0.0377)	(0.0148)				
Share Non-ICT Engineers (PCS 38 excl. ICT)					-0.0724	0.0422***	-0.0735	0.0433***
					(0.0466)	(0.0159)	(0.0469)	(0.0158)
Share Non-ICT Technicians (PCS 47 Excl. ICT)					-0.0246	0.0283	-0.0236	0.0278
					(0.0415)	(0.0183)	(0.0415)	(0.0184)
Share ICT Engineers (ICT of PCS 38)					0.0741**	0.0869***		
					(0.0376)	(0.0152)		
Share ICT Technicians (ICT of PCS 47)					-0.0643	0.0161	-0.0625	0.0172
					(0.0814)	(0.0212)	(0.0820)	(0.0211)
Share ICT Engineers R&D (PCS 388a)							0.0785*	0.0906***
							(0.0447)	(0.0177)
Share ICT Engineers Admin. & Support (PCS 388b)							-0.00486	0.0549
							(0.186)	(0.0566)
Share ICT Engineers Manager (PCS 388c)							0.129	0.0642**
							(0.0821)	(0.0288)
Share ICT Engineers Sales (PCS 388d)							-0.155	0.136***
							(0.135)	(0.0475)
Share ICT Engineers Telecom. (PCS 388e)							0.254	0.141**
							(0.178)	(0.0583)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Estimated margins for Equation 2, with the main explanatory variables being shares of workers in technical occupations. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees. All models include controls for size, age, PIK ratio, PKL ratio, physical capital, fast broadband, CRM, ERP, and E-commerce. The estimation results for these additional controls are excluded from this table but are available in Table A.2 in Appendix A

of AI machines hinge upon specialised ICT human capital, whereas basic ICT knowledge does not seem to significantly affect the probability to use AI. Second, the development of AI systems takes place in firms characterised by a higher share of non-ICT types of occupations as well. This suggests that in-depth scientific, administrative and commercial non-ICT knowledge is highly complementary to the development of AI systems.

Finally, Model 4 takes a closer look at the role of different types of ICT engineers and further analyses the association between their presence and the probability to use AI, focusing on AI buyers and developers separately. This additional disaggregation allows to investigate in further detail the role of human capital for AI buyers vs developers. The ICT-related human capital leveraged by different types of AI users partially overlaps, but also presents substantial differences. The share of ICT engineers specialised in the R&D domain is positively and significantly linked to both AI buyers and developers. The results of Table 3 are, therefore, confirmed for both buyers and developers. However, the relation estimated for the former is weaker both in magnitude and significance, suggesting that developers more strongly rely on R&D capabilities in the ICT domain.

Furthermore, AI developers also leverage several other types of ICT-related human capital. Concerning the role of telecommunications and computer networks engineers (see also Igna and Venturini, 2023), this suggests the presence of an internal digital infrastructure for managing data flows and may further explain why the presence of fast broadband connections is less frequent among developers than buyers. Furthermore, and in line with the evidence on the AI-CRM relation, the share of engineers responsible for customer relations is significantly higher in AI developers. Finally, AI developers also hinge on ICT managers, due to the fact that in-house developments of AI technologies are based on projects requiring more significant efforts in terms of financial resources and coordination.

The findings discussed in this section highlight that digital assets and human capital are key factors for the use of AI, but their relevance differ among types of AI users. This suggests that these two groups of firms make a different use of AI, which requires them to implement AI differently in production. Nonetheless, the presence of human capital related to R&D capabilities in the ICT domain is key for both AI buyers and developers, suggesting that consistent resources in innovation activities are required in order to implement and use AI systems.[17]

AI developers are characterised by a more complex mix of non-technical, technical and ICT human capital, where the latter is represented by several ICT occupations at once. First, they leverage several types of ICT occupations at one, which allow them to effectively deploy AI systems in their productive structure. This is suggested by the significant presence of engineers specialised in computer networks and ICT managers. The former are responsible for managing internal data flows at the basis of predictive AI systems. The latter point to the existence of multiple organisational layers aimed at dealing with the implementation of AI in such organisations.[18] Furthermore, its implementation by firms is still characterised by large uncertainty (Bianchini et al., 2022; Fontanelli et al., 2024) and may involve the whole firm, not just one or few of its parts (Agrawal et al., 2022). Such a complex task, involving technological as well as organisational changes, may be more easily accomplished by relying on specialised coordinators (i.e., ICT managers), with a consequent increase in the share of workers in higher intellectual occupations at the expenses of other employees (Caroli and van Reenen, 2001; Caroli et al., 2001). Second, AI developers are characterised by the presence of non-ICT technical and non-technical knowledge. This indicate that firms rely on scientific, administrative and commercial knowledge in order to develop AI systems in-house, suggesting that AI technologies leverage complex set of knowledge beyond ICT one. Finally, the significant presence of ICT engineers specialised in sales in firms developing AI suggests that these firms may sell AI solutions to other firms. Third, lower shares of workers in clerical occupations characterise AI developers. This finding is consistent with routine-biased technical change theories (Autor et al., 2003) as AI may have induced changes in the workforce composition of its users by automating the routine tasks characterising clerical workers.[19]

[17]Unreported evidence shows that results are broadly consistent with ones reported when excluding the ICT sector or ICT services (i.e., NACE 62-63). This suggests that the results concerning the link between AI development and higher intellectual occupations does not depend on ICT firms alone, as also suggested by the discussion in Section 6.2.

[18]Even though this could seem not consistent with the decentralising power of information technologies (Bloom et al., 2014), AI started to diffuse among firms at the beginning of 2010s and is a relatively young technology.

[19]This relation is unlikely due to increases in the amount of workers performing higher intellectual occupations

Conversely, AI buyers primarily rely on digital infrastructure/assets, beyond the human capital related to R&D capabilities in the ICT domain. Firms buying AI appear more likely to use their AI tools on cloud platforms, as the stronger relation with fast broadband than AI developers and not significant link with telecommunication and computer networks engineers would seem to suggest. Furthermore, they leverage more intensively on existing internal digital infrastructure, with larger coefficients estimated for CRM and a significant use of ERP software.

6.2 Heterogeneity across sectors

In this section we discuss the results of the relation between human capital and AI focusing on different sectors of the economy. We categorise firms based on the sectoral aggregation reported in Table 6. This aggregation aims to capture commonalities between more disaggregate sectors, at the same time distinguishing those characterised by key elements driving (or hindering) the diffusion of AI. It includes seven distinct macro-sectors: Manufacturing, Construction, Wholesale & Retail, Media & Telecommunications, ICT Business Services, Professional, Scientific And Technical Activities and Other Services.[20] In particular, we separate four sectors from the non-financial market services included in the survey. The Wholesale & Retail sector is indeed characterised by the presence of several large and multi-plant companies that are more likely to have extensive proprietary data at their disposal. Two ICT sectors (Media & Telecommunications and ICT Business Services) and Professional, Scientific And Technical Services have instead been distinguished from other services due to their potential role of drivers of AI innovations and use of AI softwares for consultancy activities.

Group of sectors	Sector 2–digit code (ISIC rev.4)
Manufacturing	10-33
Construction	40-43
Wholesale & Retail	45-47
Media & Telecommunications	58-61, 951
ICT Business Services	62-63
Other Services	49-56
Professional, Scientific And Technical Services	69-75

Table 6: The sectoral disaggregation used for computing shares.

We present the results examining the relationship between AI and aggregate PCS classes in Table 7. Firms in the Business ICT Services and Wholesale & Retail sectors exhibit a significant and positive association with the share of workers in higher intellectual occupations. The positive relationship remains evident in most sectors, even if this is not statistically different from zero. In contrast, the relationship is negative and largely not significant in the Construction sector. This negative association may stem from the coexistence of AI-size relations and the larger elasticities of manual workers to firm size compared to higher intellectual

because intermediate and manual occupations, despite negatively, are not significantly linked to AI use.

[20] In estimated results, we will not report firms belonging to utilities (i.e., NACE 35-39) due to the limited number of observations (79) in this sector.

AI Users, Sectors and Occupations

	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	Business ICT Services	Other Service Sectors
Share of Higher Intellectual Occupations	0.0783 (0.0593)	-0.126 (0.0956)	0.117** (0.0497)	0.0972 (0.0604)	0.0216 (0.103)	0.374*** (0.142)	0.0213 (0.0585)
Pseudo R2	.053	.104	.057	.077	.133	.161	.061
	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	Business ICT Services	Other Service Sectors
Share of Intermediate Occupations	0.0181 (0.0479)	-0.0621 (0.0607)	0.000211 (0.0418)	-0.149 (0.119)	-0.387** (0.183)	-0.120* (0.0640)	0.0876 (0.0590)
Pseudo R2	.052	.103	.052	.14	.152	.079	.063
	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	Business ICT Services	Other Service Sectors
Share of Clerical Occupations	-0.00472 (0.0553)	-0.00244 (0.106)	0.00333 (0.0289)	0.00448 (0.0627)	0.227 (0.165)	-0.212 (0.220)	0.00463 (0.0279)
Pseudo R2	.052	.101	.052	.071	.15	.136	.061
	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	Business ICT Services	Other Service Sectors
Share of Manual Workers	-0.0266 (0.0372)	0.0666 (0.0459)	-0.0451 (0.0370)	-1.121** (0.445)	-0.254 (1.518)	0.0471 (0.132)	-0.0234 (0.0259)
Pseudo R2	.052	.105	.054	.164	.132	.072	.062
Observations	2,199	914	2,156	352	233	706	1,821
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Estimated margins for Equation 1 for different sectors, with the main explanatory variables being share of aggregate PCS classes. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees. All models include controls for size, age, PIK ratio, PKL ratio, physical capital, fast broadband, CRM, ERP, and E-commerce. The estimation results for these additional controls are excluded from this table but are available in Table B.1 in Appendix A.

occupations, influenced by the manual labour-intensive nature of production in the Construction sector.[21] The relationships between other aggregate classes and sectors tend to be negative but are far from statistical significance. However, firms in the ICT sector, on average, employ fewer intermediate workers, suggesting that ICT intense AI users rely less on these occupations.

We report the results focusing on the relation between AI and technical/ICT workers across sectors in Table 5. The evidence indicates that only a few sectors may be driving the demand for technical and ICT-related human capital in response to the diffusion of AI. The share of workers in technical occupations is positive for all sectors considered, but Media & Telecommunications and Professional, Scientific and Technical Service sectors, but it is not significant across sectors. The relation between non-technical workers in higher intellectual occupations and AI in the Construction sector is negative and turns significant. This indicates that the negative relation found for the whole PCS 3 in Table 5 may be driven by differences in elasticities of output of different classes: larger output in the Construction sector implies more manual work, whose raise could crowd out high-level administrative and commercial workforce. Also, AI users in Manufacturing and

[21] Additionally, it might also result from AI applications in this sector being significantly linked to ERP software, indicating that firms in this sector primarily use AI for decision making related, for instance, to the management of building materials (see Tables A.3 and A.4).

AI Users, Sectors and Technical Occupations	Manufacturing	Construction	Wholesale & Retail	Media & Telecommunications	ICT Business Services	Prof., Scient. And Techn.	Other Service Sectors
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.156	-0.810**	0.0643	-0.149	0.171	-0.00265	-0.0125
	(0.127)	(0.322)	(0.0620)	(0.154)	(0.272)	(0.0812)	(0.0748)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.162*	-0.161*	0.00666	-0.462*	0.164	-0.00774	0.0819
	(0.0938)	(0.0919)	(0.0467)	(0.271)	(0.518)	(0.0867)	(0.0626)
Share Technical Occupations (PCS 38 and 47)	0.0712	0.0430	0.0871	-0.0572	0.220	-0.0169	0.0800
	(0.0467)	(0.0649)	(0.0539)	(0.154)	(0.221)	(0.0619)	(0.0873)
Pseudo R2	.062	.122	.055	.16	.137	.072	.063
	Manufacturing	Construction	Wholesale & Retail	Media & Telecommunications	ICT Business Services	Prof., Scient. And Techn.	Other Service Sectors
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.164	-0.808**	0.0626	-0.150	0.120	0.00579	-0.0105
	(0.127)	(0.323)	(0.0616)	(0.154)	(0.252)	(0.0790)	(0.0745)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.167*	-0.161*	0.0104	-0.456*	0.343	-0.0144	0.0817
	(0.0957)	(0.0919)	(0.0463)	(0.273)	(0.496)	(0.0846)	(0.0626)
Share Engineers (PCS 38)	-0.0213	0.0220	0.246***	-0.0355	0.337	0.108	0.0550
	(0.0707)	(0.112)	(0.0882)	(0.166)	(0.206)	(0.0713)	(0.108)
Share Technicians (PCS 47)	0.109*	0.0540	-0.0667	-0.100	-0.293	-0.231**	0.113
	(0.0579)	(0.0832)	(0.0823)	(0.178)	(0.263)	(0.109)	(0.183)
Pseudo R2	.064	.122	.06	.161	.174	.09	.063
	Manufacturing	Construction	Wholesale & Retail	Media & Telecommunications	ICT Business Services	Prof., Scient. And Techn.	Other Service Sectors
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.167	-0.796**	0.0559	-0.145	0.130	0.00516	-0.00649
	(0.126)	(0.318)	(0.0618)	(0.153)	(0.250)	(0.0782)	(0.0742)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.167*	-0.159*	0.0116	-0.454*	0.255	-0.0139	0.0842
	(0.0953)	(0.0919)	(0.0462)	(0.269)	(0.486)	(0.0831)	(0.0619)
Share Non-ICT Engineers (PCS 38 excl. ICT)	-0.0434	0.0289	0.204**	0.0220	-0.704	-0.00679	0.0414
	(0.0795)	(0.113)	(0.100)	(0.316)	(0.510)	(0.0879)	(0.182)
Share Technicians (PCS 47 excl. ICT)	0.120**	0.0783	-0.0184	-0.273	-0.188	-0.162	-1.096**
	(0.0581)	(0.0869)	(0.0927)	(0.253)	(1.280)	(0.104)	(0.434)
Share ICT Engineers (ICT of PCS 38)	0.229	-0.216	0.425**	-0.0478	0.349*	0.280***	0.00827
	(0.204)	(1.523)	(0.194)	(0.164)	(0.202)	(0.0968)	(0.153)
Share ICT Technicians (ICT of PCS 47)	-0.251	-1.280	-0.244	-0.0114	-0.275	-0.537*	0.592***
	(0.308)	(1.343)	(0.266)	(0.170)	(0.255)	(0.313)	(0.174)
Pseudo R2	.065	.124	.061	.165	.193	.105	.077
Observations	2,199	914	2,156	352	233	706	1,821
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Estimated margins for Equation 1 are presented for various sectors, with the main explanatory variables being shares of workers in technical occupations. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees. All models include controls for size, age, PIK ratio, PKL ratio, physical capital, fast broadband, CRM, ERP, and E-commerce. The estimation results for these additional controls are excluded from this table but are available in Table A.4 in Appendix A.

Professional, Scientific and Technical Services leverage less on non-technical intermediate professions.

Further disaggregations capturing the level and type of technical knowledge reveal a more nuanced picture for sector-specific relations between AI and human capital. Indeed, the share of engineers is significantly associated with AI use in the Wholesale & Retail sectors, while the share of workers in higher intellectual non-technical occupations is not significant. This suggests that the relationship between AI and higher intellectual occupations in these sectors (see Table 7) is driven by ICT workers. Additionally, AI use for firms in the Manufacturing sector is significantly and positively linked to the presence of technicians, a relation that turns negative and significant in the Professional, Scientific and Technical Service sector.

Further disaggregating technical occupations into ICT and non-ICT domains reveals that a positive and significant relationship between AI use and the share of engineers of AI users can be found three sectors, namely Wholesale & Retail, ICT Business and Professional, Scientific and Technical Service sectors. In the Wholesale & Retail sector, AI use is also positively and significantly related to non-ICT engineers, suggesting that AI users in this sector also rely on other types of highly-specialised technical occupations. Furthermore, when distinguishing ICT and non-ICT technical occupations, the relationship between AI use and the share of ICT technicians in Other Services becomes significant. This underscores the importance of the role of ICT engineers in all service sectors considered, but Media & Telecommunications. Finally, in the Manufacturing sector, AI users significantly and positively leverage technical non-ICT workers, possibly suggesting that ICT knowledge may not be as useful for AI applications by manufacturing firms as in the service sectors.

Overall, the results of Tables 7 and 8 suggest a polarisation of human capital related to the use of AI across sectors, which reflects the complementarities between AI and the sector-specific nature of production. On the one hand, AI users in most services rely on a workforce characterised by higher shares of workers in ICT occupations. This result is likely driven by complementarities between ICT knowledge and AI technologies in this sector, which is characterised by higher availability of data flows with respect to Manufacturing and Construction. For this reason, this finding hinges on the use of AI in the form of software for predictive data analysis in the service sector. However, the level of human capital leveraged by AI systems is not the same for all services. Wholesale & Retail, ICT Business and Professional, Scientific and Technical Service sectors rely on advanced ICT human capital, differently from other service sectors characterised by a higher presence of ICT technicians. This suggests that firms in services characterised by large data availability, ICT and R&D intensity rely on more complex use of AI.

On the other hand, in non-service (Manufacturing and Construction) and in the Media & Telecommunication sectors ICT-related human capital does not significantly increase the probability to use AI. First, firms using AI in the Manufacturing sector are characterised by higher shares of non-ICT technicians, suggesting that AI systems in Manufacturing are likely mostly embedded in physical machines. These do not seem to require the same in-house presence of ICT-specific human capital than services, suggesting possibly a simpler use of AI systems. Second, AI users in the Construction and Media & Telecommunication sector do not seem to rely significantly more on any kind of human capital compared to others. This suggests that AI tools in this sector may be based on business software that leverage low-demanding ICT occupations, such as ERP.

7 Concluding remarks

In this paper we carried out an in-depth analysis of the relation between human capital and AI use, using a combination of uniquely comprehensive sources of data for France. Matching four data sources – official ICT surveys, LEED, balance-sheet data, and the business registry – we provided evidence about the role of human capital for AI use. We focus on detailed occupations for a representative sample of firms and notably distinguish AI buyers vis-à-vis developers and AI-human capital relations across sectors.

Mainly focusing on a period preceding the more recent boom of generative AI, our analysis finds that human capital is strongly associated to the use of AI by firms. AI users are characterised by a larger and significant presence of higher intellectual occupations, especially ICT engineers specialised in R&D and ICT managers. Distinguishing AI buyers and developers, the analysis shows that the links between human capital and AI use relevantly differ among types of AI users. In particular, the development of AI systems appears more strongly linked to a broader set of types of ICT engineers and both technical and non-technical higher intellectual occupations beyond ICT, while AI buyers appear to mostly rely on ICT engineers specialised in R&D. This indicates that these groups of firms use and implement AI differently, because the internal development of AI systems characterises firms with several types of human capital and thus more complex occupational structures. Analysing the links between human capital and AI use in different sectors provides additional relevant insights. In services sectors, AI users are characterised by larger shares of workers specialised in the ICT domain, whereas Manufacturing firms leverages more non-ICT technicians. This is in line with the idea that in services AI is more likely integrated in software for predictive analysis, while in Manufacturing it is predominantly embedded into physical machines or tools.

Our findings are broadly consistent with the insights offered by Babina et al. (2023) on the United States, in particular about the relevance of highly-educated and STEM workers for AI use. Our analysis however expands the existing literature in several respects. In particular, other than using highly representative official sources of data beyond the United States, our work assesses the role of human capital for AI use studying the occupational structure of AI users, separating out AI buyers and developers and providing sectoral analyses. This is highly relevant also given the significant differences in returns to AI use between different groups of firms.

In fact, a broader set of occupations and a more complex organisational structure may be instrumental for AI users to realise productivity returns beyond selection, as highlighted by recent work of Calvino and Fontanelli (2023a). The relevance of a diverse set of occupations for AI developers is also in line with recent evidence on skills demand by top AI employer in the United States (Borgonovi et al., 2023), for which a combination of technical, socio-emotional and cognitive skills are evident in their AI-related online job postings.

While our analysis is comprehensive in several respects, future research may further explore the links between human capital and AI use in greater detail. In particular, future work may focus on further distinguishing the extent to which human capital is a pre-requisite for AI use from the changes in occupational composition and organisational structure that are due to the deployment of AI systems. Furthermore, ongoing efforts are aiming at exploring related research questions also in other countries and analysing more broadly the complementarities between human capital, AI, and other digital technologies. Finally, future work may extend the present analysis to further consider the extent to which human capital is instrumental in realising the productivity potential of AI.

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A Additional tables

AI Users and Technical Occupations

	Technical Occupations		Eng. & Technicians		ICT Eng. & ICT Technicians		Disaggregate ICT Engineers	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.0397	0.0109	0.0442	0.0171	0.0505	0.0218	0.0513	0.0229
	(0.0317)	(0.0329)	(0.0317)	(0.0329)	(0.0319)	(0.0331)	(0.0319)	(0.0331)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	0.00454	-0.00348	0.00791	0.000260	0.00919	0.00198	0.00911	0.00180
	(0.0294)	(0.0301)	(0.0292)	(0.0299)	(0.0289)	(0.0296)	(0.0289)	(0.0296)
Share Technical Occupations (PCS 38 and 47)	0.0490**	0.0302						
	(0.0231)	(0.0235)						
Share Engineers (PCS 38)			0.109***	0.0886***				
			(0.0292)	(0.0297)				
Share Technicians (PCS 47)			-0.0293	-0.0445				
			(0.0377)	(0.0382)				
Share Non-ICT Engineers (PCS 38 excl. ICT)					0.0132	-0.00777	0.0146	-0.00620
					(0.0427)	(0.0430)	(0.0427)	(0.0429)
Share Non-ICT Technicians (PCS 47 Excl. ICT)					-0.0119	-0.0179	-0.0127	-0.0186
					(0.0421)	(0.0428)	(0.0421)	(0.0429)
Share ICT Engineers (ICT of PCS 38)					0.192***	0.170***		
					(0.0388)	(0.0394)		
Share ICT Technicians (ICT of PCS 47)					-0.00517	-0.0481	-0.00122	-0.0426
					(0.0740)	(0.0743)	(0.0741)	(0.0741)
Share ICT Engineers R&D (PCS 388a)							0.204***	0.186***
							(0.0480)	(0.0484)
Share ICT Engineers Admin. & Support (PCS 388b)							0.0860	0.0139
							(0.164)	(0.166)
Share ICT Engineers Manager (PCS 388c)							0.157**	0.146*
							(0.0800)	(0.0803)
Share ICT Engineers Sales (PCS 388d)							0.292**	0.229
							(0.148)	(0.145)
Share ICT Engineers Telecom. (PCS 388e)							0.194	0.219
							(0.176)	(0.171)
Log Sales	0.0102***	-0.00225	0.00908***	-0.00366	0.00949***	-0.00302	0.00951***	-0.00312
	(0.00307)	(0.00698)	(0.00309)	(0.00692)	(0.00309)	(0.00692)	(0.00308)	(0.00691)
Log Age	-0.0117*	-0.0123*	-0.0105	-0.0110*	-0.00937	-0.0105	-0.00925	-0.0105
	(0.00644)	(0.00669)	(0.00644)	(0.00670)	(0.00645)	(0.00670)	(0.00645)	(0.00670)
PIK Ratio		-0.00393		-0.00371		-0.00420		-0.00435
		(0.00424)		(0.00422)		(0.00421)		(0.00422)
PKL ratio		-0.00465		-0.00513		-0.00338		-0.00337
		(0.00763)		(0.00761)		(0.00760)		(0.00761)
Log Physical Capital		0.00700		0.00765		0.00675		0.00685
		(0.00787)		(0.00781)		(0.00783)		(0.00782)
Multi-plant		0.000720		0.00144		0.00204		0.00200
		(0.00978)		(0.00976)		(0.00972)		(0.00972)
Exporter		0.00558		0.00361		0.00545		0.00556
		(0.0107)		(0.0108)		(0.0107)		(0.0107)
Fast Broadband		0.0294**		0.0285**		0.0273**		0.0277**
		(0.0120)		(0.0120)		(0.0120)		(0.0119)
CRM		0.0412***		0.0405***		0.0398***		0.0399***
		(0.00987)		(0.00988)		(0.00987)		(0.00987)
ERP		0.0200*		0.0204**		0.0210**		0.0209**
		(0.0102)		(0.0102)		(0.0102)		(0.0102)
E-Commerce		0.00808		0.00881		0.00927		0.00940
		(0.0124)		(0.0124)		(0.0124)		(0.0124)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.032	.043	.034	.045	.037	.048	.037	.048

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

Table A.1: Estimated margins for Equation 1, with the main explanatory variables being shares of workers in technical occupations. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

AI Buyers, AI Developers and Technical Occupations

	Technical Occupations Model 1		Eng. & Technicians Model 2		ICT Eng. & ICT Technicians Model 3		Disaggregate ICT Engineers Model 4	
	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer	AI Buyer	AI Developer
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	-0.00735	0.0305**	-0.00491	0.0337**	-0.00156	0.0348**	-0.00109	0.0351**
	(0.0306)	(0.0144)	(0.0306)	(0.0145)	(0.0309)	(0.0144)	(0.0309)	(0.0144)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.00599	-0.00125	-0.00448	0.000913	-0.00307	0.00156	-0.00348	0.00170
	(0.0283)	(0.0153)	(0.0283)	(0.0150)	(0.0282)	(0.0148)	(0.0281)	(0.0147)
Share Technical Occupations (PCS 38 and 47)	-0.0177	0.0496***						
	(0.0236)	(0.00982)						
Share Engineers (PCS 38)			0.00776	0.0687***				
			(0.0292)	(0.0122)				
Share Technicians (PCS 47)			-0.0488	0.0193				
			(0.0377)	(0.0148)				
Share Non-ICT Engineers (PCS 38 excl. ICT)					-0.0724	0.0422***	-0.0735	0.0433***
					(0.0466)	(0.0159)	(0.0469)	(0.0158)
Share Non-ICT Technicians (PCS 47 Excl. ICT)					-0.0246	0.0283	-0.0236	0.0278
					(0.0415)	(0.0183)	(0.0415)	(0.0184)
Share ICT Engineers (ICT of PCS 38)					0.0741**	0.0869***		
					(0.0376)	(0.0152)		
Share ICT Technicians (ICT of PCS 47)					-0.0643	0.0161	-0.0625	0.0172
					(0.0814)	(0.0212)	(0.0820)	(0.0211)
Share ICT Engineers R&D (PCS 388a)							0.0785*	0.0906***
							(0.0447)	(0.0177)
Share ICT Engineers Admin. & Support (PCS 388b)							-0.00486	0.0549
							(0.186)	(0.0566)
Share ICT Engineers Manager (PCS 388c)							0.129	0.0642**
							(0.0821)	(0.0288)
Share ICT Engineers Sales (PCS 388d)							-0.155	0.136***
							(0.135)	(0.0475)
Share ICT Engineers Telecom. (PCS 388e)							0.254	0.141**
							(0.178)	(0.0583)
Log Sales	-0.000172	-0.000302	-0.000735	-0.00110	-0.000176	-0.000973	-0.000138	-0.00113
	(0.00657)	(0.00316)	(0.00657)	(0.00310)	(0.00660)	(0.00307)	(0.00660)	(0.00305)
Log Age	-0.00686	-0.0119***	-0.00635	-0.0111***	-0.00595	-0.0108***	-0.00619	-0.0106***
	(0.00643)	(0.00297)	(0.00646)	(0.00297)	(0.00649)	(0.00293)	(0.00649)	(0.00295)
PIK Ratio	-0.00406	-0.00189	-0.00396	-0.00192	-0.00435	-0.00210	-0.00468	-0.00199
	(0.00399)	(0.00190)	(0.00399)	(0.00188)	(0.00398)	(0.00186)	(0.00399)	(0.00186)
PKL ratio	0.00283	-0.00558	0.00264	-0.00569	0.00399	-0.00508	0.00428	-0.00537
	(0.00711)	(0.00378)	(0.00711)	(0.00372)	(0.00713)	(0.00369)	(0.00714)	(0.00370)
Log Physical Capital	0.000892	0.00652*	0.00113	0.00689*	0.000405	0.00657*	0.000276	0.00672*
	(0.00737)	(0.00378)	(0.00735)	(0.00370)	(0.00739)	(0.00369)	(0.00739)	(0.00368)
Multi-plant	-0.00282	0.00694	-0.00252	0.00731	-0.00220	0.00745	-0.00216	0.00762*
	(0.00932)	(0.00462)	(0.00932)	(0.00458)	(0.00930)	(0.00455)	(0.00930)	(0.00454)
Exporter	0.00195	0.000465	0.00111	-0.000627	0.00258	2.95e-05	0.00269	5.65e-06
	(0.0103)	(0.00486)	(0.0103)	(0.00490)	(0.0103)	(0.00484)	(0.0103)	(0.00484)
Fast Broadband	0.0276**	0.00741	0.0272**	0.00701	0.0261**	0.00663	0.0262**	0.00681
	(0.0114)	(0.00518)	(0.0114)	(0.00516)	(0.0114)	(0.00512)	(0.0114)	(0.00512)
CRM	0.0310***	0.0248***	0.0308***	0.0244***	0.0303***	0.0241***	0.0308***	0.0239***
	(0.00952)	(0.00474)	(0.00954)	(0.00470)	(0.00955)	(0.00463)	(0.00953)	(0.00462)
ERP	0.0187*	0.00186	0.0189*	0.00216	0.0196**	0.00241	0.0198**	0.00226
	(0.00979)	(0.00463)	(0.00979)	(0.00459)	(0.00975)	(0.00453)	(0.00974)	(0.00452)
E-Commerce	0.00338	0.00763	0.00368	0.00796	0.00401	0.00808	0.00392	0.00829
	(0.0119)	(0.00535)	(0.0119)	(0.00530)	(0.0119)	(0.00527)	(0.0119)	(0.00528)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes

Table A.2: Estimated margins for Equation 2, with the main explanatory variables being shares of workers in technical occupations. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

AI Users, Sectors and Occupations

	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	ICT Business Services	Other Service Sectors	Manufacturing	Construction	Wholesale Retail	Telecommunications Telecommunications	ICT Business Sector	Prof., Scient. And Techn.	Other Service Sectors
				Higher Intellectual Occupations							Intermediate Occupations			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Share	0.0783	-0.126	0.117**	0.0972	0.0216	0.374***	0.0213	0.0181	-0.0621	0.000211	-0.149	-0.387**	-0.120*	0.0876
	(0.0593)	(0.0956)	(0.0497)	(0.0604)	(0.103)	(0.142)	(0.0585)	(0.0479)	(0.0607)	(0.0418)	(0.119)	(0.183)	(0.0640)	(0.0590)
Log Sales	0.00606	-0.0109	-0.00478	0.0278	-0.0694**	-0.0223	-0.0153	0.00763	-0.0135	0.00166	-0.0674**	-0.00749	0.0329*	-0.0159
	(0.0111)	(0.0214)	(0.0123)	(0.0193)	(0.0343)	(0.0618)	(0.0134)	(0.0110)	(0.0197)	(0.0119)	(0.0337)	(0.0607)	(0.0190)	(0.0129)
Log Age	-0.0290**	-0.0157	0.00327	0.0318	-0.0417	-0.0301	-0.0134	-0.0292**	-0.0151	0.00162	-0.0427	-0.0550	0.0301	-0.0129
	(0.0116)	(0.0172)	(0.0121)	(0.0259)	(0.0349)	(0.0662)	(0.0128)	(0.0116)	(0.0171)	(0.0122)	(0.0349)	(0.0659)	(0.0262)	(0.0127)
PIK Ratio	0.00182	0.00586	-0.00834	-0.000777	-0.00870	0.0276	-0.0142	0.000962	0.00681	-0.00992	-0.00994	0.0272	-0.000264	-0.0149*
	(0.00896)	(0.00954)	(0.00883)	(0.0141)	(0.0179)	(0.0224)	(0.00918)	(0.00891)	(0.00957)	(0.00891)	(0.0175)	(0.0225)	(0.0142)	(0.00893)
PKL ratio	-0.0117	-0.0108	-0.0110	0.0126	-0.0382	0.0307	-0.00386	-0.0118	-0.0137	-0.00448	-0.0379	0.0312	0.0105	-0.00449
	(0.0130)	(0.0229)	(0.0164)	(0.0255)	(0.0442)	(0.0634)	(0.0129)	(0.0128)	(0.0217)	(0.0158)	(0.0453)	(0.0627)	(0.0258)	(0.0125)
Log Physical Capital	0.00994	0.0165	0.0182	-0.0281	0.0827**	0.00316	0.00910	0.00953	0.0192	0.0118	0.0813**	-0.00625	-0.0276	0.00951
	(0.0124)	(0.0253)	(0.0158)	(0.0243)	(0.0407)	(0.0666)	(0.0143)	(0.0122)	(0.0239)	(0.0153)	(0.0410)	(0.0648)	(0.0245)	(0.0137)
Multi-plant	-0.0185	-0.0427*	0.00573	0.0376	-0.0341	0.114	0.0124	-0.0183	-0.0409	0.00328	-0.0414	0.121	0.0297	0.00871
	(0.0177)	(0.0251)	(0.0190)	(0.0333)	(0.0638)	(0.0819)	(0.0201)	(0.0177)	(0.0253)	(0.0190)	(0.0676)	(0.0832)	(0.0332)	(0.0203)
Exporter	-0.00963	0.0247	-0.0156	0.0351	0.0753	0.0178	0.0182	-0.00666	0.0171	-0.00491	0.0722	0.0135	0.0415	0.0179
	(0.0202)	(0.0286)	(0.0198)	(0.0382)	(0.0570)	(0.0854)	(0.0220)	(0.0202)	(0.0290)	(0.0194)	(0.0550)	(0.0857)	(0.0383)	(0.0216)
Fast Broadband	0.0446*	-0.0169	0.0715***	-0.0251	0.0160	0.0543	0.0323	0.0474**	-0.0238	0.0779***	0.0210	0.0489	-0.0225	0.0292
	(0.0238)	(0.0402)	(0.0235)	(0.0358)	(0.0513)	(0.0801)	(0.0264)	(0.0233)	(0.0398)	(0.0232)	(0.0516)	(0.0806)	(0.0360)	(0.0258)
CRM	0.00308	0.0297	0.0304	0.0946***	0.0789	0.156*	0.0591***	0.00461	0.0324	0.0348*	0.0735	0.158*	0.0915**	0.0548***
	(0.0172)	(0.0275)	(0.0188)	(0.0359)	(0.0557)	(0.0862)	(0.0203)	(0.0169)	(0.0280)	(0.0187)	(0.0564)	(0.0862)	(0.0361)	(0.0204)
ERP	0.00856	0.0628***	-0.0306	-0.0115	0.0924*	0.0375	0.0496***	0.0110	0.0619***	-0.0274	0.106**	0.0470	-0.0121	0.0484***
	(0.0202)	(0.0230)	(0.0196)	(0.0372)	(0.0558)	(0.0865)	(0.0188)	(0.0206)	(0.0232)	(0.0194)	(0.0536)	(0.0875)	(0.0377)	(0.0187)
E-Commerce	0.0222	-0.176***	-0.0140	0.127*	-0.00320	0.0581	0.0261	0.0214	-0.174***	-0.0180	-0.0129	0.0488	0.119*	0.0273
	(0.0235)	(0.0537)	(0.0200)	(0.0662)	(0.0636)	(0.129)	(0.0228)	(0.0234)	(0.0526)	(0.0200)	(0.0640)	(0.125)	(0.0660)	(0.0227)
Observations	2,199	914	2,156	706	352	233	1,821	2,199	914	2,156	352	233	706	1,821
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.053	.104	.057	.077	.133	.161	.061	.052	.103	.052	.14	.152	.079	.063

	Manufacturing	Construction	Wholesale & Retail	Prof., Scient. And Techn.	Media & Telecommunications	ICT Business Services	Other Service Sectors	Manufacturing	Construction	Wholesale Retail	Telecommunications Telecommunications	ICT Business Sector	Prof., Scient. And Techn.	Other Service Sectors
				Clerical Occupations							Manual Occupations			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Share	-0.00472	-0.00244	0.00333	0.00448	0.227	-0.212	0.00463	-0.0266	0.0666	-0.0451	-1.121**	-0.254	0.0471	-0.0234
	(0.0553)	(0.106)	(0.0289)	(0.0627)	(0.165)	(0.220)	(0.0279)	(0.0372)	(0.0459)	(0.0370)	(0.445)	(1.518)	(0.132)	(0.0259)
Log Sales	0.00833	-0.0167	0.00181	0.0348*	-0.0665**	-0.00210	-0.0135	0.00672	-0.00926	0.000463	-0.0871**	0.00702	0.0349*	-0.0152
	(0.0110)	(0.0189)	(0.0121)	(0.0198)	(0.0324)	(0.0649)	(0.0128)	(0.0111)	(0.0212)	(0.0121)	(0.0408)	(0.0629)	(0.0194)	(0.0129)
Log Age	-0.0292**	-0.0153	0.00171	0.0260	-0.0509	-0.0619	-0.0132	-0.0290**	-0.0145	0.00345	-0.0369	-0.0763	0.0267	-0.0122
	(0.0116)	(0.0171)	(0.0122)	(0.0269)	(0.0355)	(0.0680)	(0.0130)	(0.0116)	(0.0169)	(0.0122)	(0.0335)	(0.0667)	(0.0270)	(0.0129)
PIK Ratio	0.000983	0.00652	-0.00991	-0.000551	-0.0119	0.0325	-0.0147*	0.00135	0.00686	-0.00868	-0.00767	0.0319	-0.000568	-0.0143
	(0.00887)	(0.00965)	(0.00886)	(0.0143)	(0.0176)	(0.0227)	(0.00890)	(0.00886)	(0.00960)	(0.00875)	(0.0178)	(0.0226)	(0.0143)	(0.00907)
PKL ratio	-0.0116	-0.0139	-0.00424	0.0133	-0.0633	0.0228	-0.00256	-0.0125	-0.00912	-0.00440	-0.0628	0.0245	0.0139	-0.00569
	(0.0130)	(0.0220)	(0.0161)	(0.0258)	(0.0442)	(0.0662)	(0.0124)	(0.0129)	(0.0232)	(0.0160)	(0.0482)	(0.0655)	(0.0259)	(0.0127)
Log Physical Capital	0.00889	0.0203	0.0116	-0.0286	0.101**	-0.00383	0.00754	0.0108	0.0141	0.0122	0.109**	-0.0101	-0.0293	0.0101
	(0.0125)	(0.0237)	(0.0156)	(0.0247)	(0.0412)	(0.0702)	(0.0136)	(0.0124)	(0.0256)	(0.0155)	(0.0471)	(0.0686)	(0.0249)	(0.0138)
Multi-plant	-0.0179	-0.0425*	0.00319	0.0295	-0.0778	0.107	0.0128	-0.0200	-0.0385	0.00468	-0.0256	0.111	0.0291	0.0118
	(0.0180)	(0.0254)	(0.0190)	(0.0335)	(0.0559)	(0.0861)	(0.0202)	(0.0178)	(0.0253)	(0.0189)	(0.0660)	(0.0870)	(0.0333)	(0.0200)
Exporter	-0.00677	0.0187	-0.00444	0.0433	0.0735	0.0262	0.0191	-0.00645	0.0207	-0.00223	0.0741	0.0247	0.0425	0.0222
	(0.0202)	(0.0287)	(0.0197)	(0.0378)	(0.0528)	(0.0876)	(0.0221)	(0.0203)	(0.0287)	(0.0196)	(0.0552)	(0.0871)	(0.0377)	(0.0223)
Fast Broadband	0.0480**	-0.0216	0.0781***	-0.0210	0.0343	0.0404	0.0337	0.0449*	-0.0214	0.0762***	0.0103	0.0354	-0.0201	0.0311
	(0.0226)	(0.0399)	(0.0233)	(0.0359)	(0.0510)	(0.0819)	(0.0261)	(0.0229)	(0.0398)	(0.0231)	(0.0508)	(0.0826)	(0.0360)	(0.0260)
CRM	0.00499	0.0274	0.0349*	0.0976***	0.0761	0.148	0.0596***	0.00394	0.0367	0.0337*	0.0519	0.149	0.0992***	0.0568***
	(0.0169)	(0.0277)	(0.0188)	(0.0362)	(0.0563)	(0.0902)	(0.0202)	(0.0170)	(0.0284)	(0.0186)	(0.0564)	(0.0907)	(0.0364)	(0.0203)
ERP	0.0114	0.0600***	-0.0271	-0.00762	0.103**	0.0536	0.0502***	0.0106	0.0646***	-0.0259	0.101*	0.0584	-0.00746	0.0505***
	(0.0205)	(0.0228)	(0.0194)	(0.0377)	(0.0522)	(0.0905)	(0.0190)	(0.0205)	(0.0233)	(0.0194)	(0.0528)	(0.0902)	(0.0378)	(0.0189)
E-Commerce	0.0218	-0.170***	-0.0185	0.116*	-0.0293	0.0749	0.0244	0.0188	-0.176***	-0.0228	0.0110	0.0694	0.116*	0.0214
	(0.0233)	(0.0514)	(0.0204)	(0.0670)	(0.0655)	(0.131)	(0.0235)	(0.0237)	(0.0541)	(0.0198)	(0.0617)	(0.130)	(0.0673)	(0.0233)
Observations	2,199	914	2,156	706	352	233	1,821	2,199	914	2,156	352	233	706	1,821
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.052	.101	.052	.071	.15	.136	.061	.052	.105	.054	.164	.132	.072	.062

Table A.3: Estimated margins for Equation 1 for different sectors, with the main explanatory variables being share of aggregate PCS classes. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

AI Users, Sectors and Technical Occupations

	Manufacturing Model 1	Construction Model 2	Wholesale & Retail Model 3	Media & Telecommunications Model 4	ICT Business Services Model 5	Prof., Scient. And Techn. Model 6	Other Service Sectors Model 7
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.156	-0.810**	0.0643	-0.149	0.171	-0.00265	-0.0125
	(0.127)	(0.322)	(0.0620)	(0.154)	(0.272)	(0.0812)	(0.0748)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.162*	-0.161*	0.00666	-0.462*	0.164	-0.00774	0.0819
	(0.0938)	(0.0919)	(0.0467)	(0.271)	(0.518)	(0.0867)	(0.0626)
Share Technical Occupations (PCS 38 and 47)	0.0712	0.0430	0.0871	-0.0572	0.220	-0.0169	0.0800
	(0.0467)	(0.0649)	(0.0539)	(0.154)	(0.221)	(0.0619)	(0.0873)
Log Sales	0.00624	-0.0104	-0.00171	-0.0577*	-0.000744	0.0345*	-0.0177
	(0.0109)	(0.0213)	(0.0124)	(0.0328)	(0.0646)	(0.0202)	(0.0135)
Log Age	-0.0280**	-0.0148	0.00140	-0.0392	-0.0631	0.0251	-0.0127
	(0.0115)	(0.0173)	(0.0122)	(0.0360)	(0.0682)	(0.0263)	(0.0128)
PIK Ratio	0.000798	0.00678	-0.00920	-0.0157	0.0317	-0.000442	-0.0146
	(0.00894)	(0.00957)	(0.00894)	(0.0167)	(0.0228)	(0.0144)	(0.00919)
PKL ratio	-0.0106	-0.0130	-0.00731	-0.0374	0.0270	0.0123	-0.00543
	(0.0128)	(0.0227)	(0.0163)	(0.0433)	(0.0675)	(0.0259)	(0.0130)
Log Physical Capital	0.00965	0.0197	0.0153	0.0789*	-0.00515	-0.0275	0.0106
	(0.0123)	(0.0251)	(0.0157)	(0.0415)	(0.0704)	(0.0249)	(0.0143)
Multi-plant	-0.0178	-0.0460*	0.00559	-0.0713	0.105	0.0292	0.00977
	(0.0178)	(0.0252)	(0.0190)	(0.0533)	(0.0861)	(0.0333)	(0.0202)
Exporter	-0.0103	0.0210	-0.0124	0.0721	0.0292	0.0447	0.0171
	(0.0200)	(0.0290)	(0.0198)	(0.0527)	(0.0889)	(0.0379)	(0.0217)
Fast Broadband	0.0437*	-0.0274	0.0734***	0.0366	0.0371	-0.0210	0.0285
	(0.0237)	(0.0398)	(0.0235)	(0.0502)	(0.0829)	(0.0361)	(0.0256)
CRM	0.00157	0.0420	0.0314*	0.0518	0.149	0.0970***	0.0560***
	(0.0172)	(0.0280)	(0.0187)	(0.0554)	(0.0909)	(0.0362)	(0.0204)
ERP	0.00701	0.0582**	-0.0312	0.102**	0.0534	-0.00788	0.0479**
	(0.0203)	(0.0229)	(0.0197)	(0.0514)	(0.0913)	(0.0377)	(0.0187)
E-Commerce	0.0295	-0.178***	-0.0144	-0.00488	0.0740	0.115*	0.0281
	(0.0239)	(0.0551)	(0.0199)	(0.0676)	(0.130)	(0.0667)	(0.0227)
Observations	2,199	914	2,156	352	233	706	1,821
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.062	.122	.055	.16	.137	.072	.063

	Manufacturing Model 1	Construction Model 2	Wholesale & Retail Model 3	Media & Telecommunications Model 4	ICT Business Services Model 5	Prof., Scient. And Techn. Model 6	Other Service Sectors Model 7
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.164	-0.808**	0.0626	-0.150	0.120	0.00579	-0.0105
	(0.127)	(0.323)	(0.0616)	(0.154)	(0.252)	(0.0790)	(0.0745)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.167*	-0.161*	0.0104	-0.456*	0.343	-0.0144	0.0817
	(0.0957)	(0.0919)	(0.0463)	(0.273)	(0.496)	(0.0846)	(0.0626)
Share ICT Engineers (ICT of PCS 38)	-0.0213	0.0220	0.246***	-0.0355	0.337	0.108	0.0550
	(0.0707)	(0.112)	(0.0882)	(0.166)	(0.206)	(0.0713)	(0.108)
Share ICT Technicians (ICT of PCS 47)	0.109*	0.0540	-0.0667	-0.100	-0.293	-0.231**	0.113
	(0.0579)	(0.0832)	(0.0823)	(0.178)	(0.263)	(0.109)	(0.183)
Log Sales	0.00599	-0.00992	-0.00437	-0.0584*	-0.0227	0.0253	-0.0171
	(0.0109)	(0.0217)	(0.0123)	(0.0330)	(0.0596)	(0.0195)	(0.0134)
Log Age	-0.0285**	-0.0150	0.00409	-0.0376	-0.0152	0.0334	-0.0127
	(0.0116)	(0.0174)	(0.0121)	(0.0364)	(0.0659)	(0.0249)	(0.0128)
PIK Ratio	-0.000337	0.00667	-0.00792	-0.0150	0.0274	0.00184	-0.0147
	(0.00896)	(0.00957)	(0.00884)	(0.0169)	(0.0225)	(0.0140)	(0.00921)
PKL ratio	-0.0117	-0.0124	-0.0120	-0.0376	0.0514	0.00933	-0.00507
	(0.0126)	(0.0232)	(0.0162)	(0.0434)	(0.0645)	(0.0251)	(0.0130)
Log Physical Capital	0.0113	0.0193	0.0188	0.0780*	-0.00973	-0.0245	0.0102
	(0.0121)	(0.0254)	(0.0155)	(0.0415)	(0.0654)	(0.0239)	(0.0143)
Multi-plant	-0.0179	-0.0462*	0.00562	-0.0701	0.134*	0.0305	0.00952
	(0.0178)	(0.0252)	(0.0190)	(0.0531)	(0.0795)	(0.0330)	(0.0203)
Exporter	-0.00767	0.0220	-0.0170	0.0696	0.0107	0.0397	0.0169
	(0.0201)	(0.0288)	(0.0199)	(0.0535)	(0.0873)	(0.0388)	(0.0217)
Fast Broadband	0.0453*	-0.0266	0.0707***	0.0363	0.0653	-0.0207	0.0280
	(0.0237)	(0.0401)	(0.0235)	(0.0500)	(0.0799)	(0.0355)	(0.0255)
CRM	0.00149	0.0420	0.0283	0.0512	0.149*	0.0871**	0.0559***
	(0.0171)	(0.0279)	(0.0189)	(0.0552)	(0.0849)	(0.0366)	(0.0205)
ERP	0.00786	0.0585**	-0.0314	0.106**	0.0481	-0.0101	0.0477**
	(0.0202)	(0.0228)	(0.0196)	(0.0523)	(0.0848)	(0.0374)	(0.0187)
E-Commerce	0.0298	-0.179***	-0.0155	-0.00476	0.0556	0.138**	0.0280
	(0.0239)	(0.0556)	(0.0198)	(0.0680)	(0.125)	(0.0660)	(0.0227)
Observations	2,199	914	2,156	352	233	706	1,821
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.064	.122	.06	.161	.174	.09	.063

	Manufacturing Model 1	Construction Model 2	Wholesale & Retail Model 3	Media & Telecommunications Model 4	ICT Business Services Model 5	Prof., Scient. And Techn. Model 6	Other Service Sectors Model 7
Share Non-Tech. Higher Intellectual Occupations (PCS 3 excl. 38)	0.167	-0.796**	0.0559	-0.145	0.130	0.00516	-0.00649
	(0.126)	(0.318)	(0.0618)	(0.153)	(0.250)	(0.0782)	(0.0742)
Share Non-Tech. Intermediate Occupations (PCS 4 excl. 47)	-0.167*	-0.159*	0.0116	-0.454*	0.255	-0.0139	0.0842
	(0.0953)	(0.0919)	(0.0462)	(0.269)	(0.486)	(0.0831)	(0.0619)
Share ICT Engineers (ICT of PCS 38)	-0.0434	0.0289	0.204**	0.0220	-0.704	-0.00679	0.0414
	(0.0795)	(0.113)	(0.100)	(0.316)	(0.510)	(0.0879)	(0.182)
Share ICT Technicians (ICT of PCS 47)	0.120**	0.0783	-0.0184	-0.273	-0.188	-0.162	-1.096**
	(0.0581)	(0.0869)	(0.0927)	(0.253)	(1.280)	(0.104)	(0.434)
Share PCS 38 (only ICT)	0.229	-0.216	0.425**	-0.0478	0.349*	0.280***	0.00827
	(0.204)	(1.523)	(0.194)	(0.164)	(0.202)	(0.0968)	(0.153)
Share PCS 47 (only ICT)	-0.251	-1.280	-0.244	-0.0114	-0.275	-0.537*	0.592***
	(0.308)	(1.343)	(0.266)	(0.170)	(0.255)	(0.313)	(0.174)
Log Sales	0.00570	-0.0113	-0.00379	-0.0593*	-0.0356	0.0270	-0.0131
	(0.0109)	(0.0217)	(0.0123)	(0.0327)	(0.0600)	(0.0197)	(0.0134)
Log Age	-0.0284**	-0.0156	0.00493	-0.0373	-0.00282	0.0368	-0.0116
	(0.0116)	(0.0174)	(0.0121)	(0.0358)	(0.0644)	(0.0246)	(0.0127)
PIK Ratio	-7.29e-05	0.00683	-0.00772	-0.0158	0.0222	-0.000953	-0.0138
	(0.00894)	(0.00962)	(0.00885)	(0.0168)	(0.0226)	(0.0138)	(0.00928)
PKL ratio	-0.0116	-0.0148	-0.0108	-0.0369	0.0444	0.0166	-0.00464
	(0.0125)	(0.0233)	(0.0162)	(0.0430)	(0.0644)	(0.0255)	(0.0130)
Log Physical Capital	0.0112	0.0219	0.0173	0.0798*	0.00187	-0.0269	0.00993
	(0.0121)	(0.0257)	(0.0154)	(0.0410)	(0.0672)	(0.0242)	(0.0144)
Multi-plant	-0.0181	-0.0459*	0.00562	-0.0722	0.116	0.0318	0.0160
	(0.0177)	(0.0252)	(0.0189)	(0.0534)	(0.0765)	(0.0324)	(0.0200)
Exporter	-0.00737	0.0219	-0.0169	0.0744	0.0125	0.0375	0.0153
	(0.0200)	(0.0289)	(0.0199)	(0.0541)	(0.0845)	(0.0382)	(0.0216)
Fast Broadband	0.0455*	-0.0256	0.0707***	0.0402	0.0518	-0.0288	0.0181
	(0.0236)	(0.0402)	(0.0237)	(0.0493)	(0.0767)	(0.0354)	(0.0259)
CRM	0.00238	0.0413	0.0301	0.0389	0.139	0.0760**	0.0581***
	(0.0169)	(0.0279)	(0.0188)	(0.0544)	(0.0851)	(0.0359)	(0.0202)
ERP	0.00865	0.0575**	-0.0310	0.109**	0.0300	-0.00394	0.0459**
	(0.0202)	(0.0228)	(0.0196)	(0.0516)	(0.0833)	(0.0367)	(0.0185)
E-Commerce	0.0287	-0.181***	-0.0155	-0.00288	0.0622	0.140**	0.0283
	(0.0238)	(0.0550)	(0.0198)	(0.0674)	(0.124)	(0.0645)	(0.0224)
Observations	2,199	914	2,156	352	233	706	1,821
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.065	.124	.061	.165	.193	.105	.077

Table A.4: Estimated margins for Equation 1 for different sectors, with the main explanatory variables being share of aggregate PCS classes. Observations are weighted using sample weights provided by the French ICT survey, making them representative of the population of French firms with more than 10 employees.

B The AI-human capital relation when AI use was not possible

Numerous significant advancements in AI applications and technologies occurred in 2012, exemplified by the development of the AlexNet neural network (see AlexNet). The advancements in AI applications and technologies from 2012 onwards marked a turning point in the field. The subsequent years witnessed a significant acceleration in the development and application of deep learning and artificial neural networks, leading to substantial improvements in various AI related tasks. The use of deep learning and artificial neural networks began to surpass state-of-the-art non-AI related techniques in statistical analyses (see also references here, here, and Babina et al., 2021). Consequently, the surge in AI adoption by firms most likely commenced after 2011 in the United States. While the United States often leads in early technology adoption, the diffusion of AI technologies in other countries, including France, may have followed with some time lag.

In order to gauge whether the results discussed in Section 5 indicate that higher intellectual occupations and, in particular, specialised ICT skills are relevant factor for the diffusion of AI across firms, we run a further regression analysis. We estimate a Probit model using data on shares and firm characteristics in 2011, when the use of AI could not affect these factors:

$$\Pr(\text{AI User}_{i,2018}) = \Phi(\text{Occup. Shares}_{i,2011}, \text{Firm Char.}_{i,2011}, \text{Dig. Controls}_{i,2018}, \text{Industry}_i, \text{Region}_i) \tag{B.1}$$

Where the chosen variables are the same of Equation 1.

We report the results of Equation B.1 estimation in Table B.1. The shares of workers in higher intellectual occupations and other aggregate occupational categories in 2011 are not significantly linked to AI use (Models 1-4). However, similarly to results discussed in Section 5, firms using AI leverage ICT engineers before AI use was possible (Model 7). When studying the most granular classification allowed by our data, Model 8 of Table B.1 reveal that AI use is related to the presence of ICT engineers specialised in administration and support and ICT managers. The estimation results reported by Model 9, using the sample of firms from Models 1-8, show that results correspond in terms of relevance of aggregate ICT engineers. However, the type of ICT human capital leveraged by AI users changed in time. The share of ICT engineers specialised in R&D is indeed significant only when 2018 shares are used.

The results reported on Table B.1 suggest that AI users were leveraging advanced ICT human capital before AI use was possible, indicating the possible presence of self-selection into AI use (Calvino and Fontanelli, 2023a,b). Furthermore, our findings also indicate that the type of human capital leveraged by AI users changed in time, with R&D capabilities in the ICT domain gaining importance relative to the period in which AI use was not possible.

C 4-digits of ICT engineers

In this section we delve into the definition of 4-digits classes of engineers provided by the 2003 PCS classification:

- ICT Engineer. R&D (PCS 388a): Engineers and executives in the private sector, involved in the study and development of computer systems and applications, including technical design, programming, configuration, debugging, or documentation of programs in compliance with current standards in the professional environment.
- ICT Engineer, Administration & Support (PCS 388b): Engineers and executives in the private sector responsible for the operation and monitoring of computer equipment and providing assistance to various users. Their goal is to implement and optimise the use of information system applications. They typically advise management in software and hardware selection.
- ICT Engineer, Manager (PCS 388c): Engineers and executives in the private sector responsible for negotiating and prescribing IT solutions, organising, managing resources, and overseeing prescribed

	2011 Shares								2018 Shares	
	Higher Intellectual Occupations Model 1	Intermediate Occupations Model 2	Clerical Occupations Model 3	Manual Occupations Model 4	Technical Occupations Model 5	Eng. & Technicians Model 6	ICT Eng. & ICT Technicians Model 7	Disaggregate ICT Eng. Model 8	ICT Eng. & ICT Technicians Model 9	Disaggregate ICT Eng. Model 10
Share	0.0304	-0.0308	0.0255	-0.0217						
	(0.0258)	(0.0253)	(0.0210)	(0.0206)						
Share Higher Intellectual Professions (PCS 3 excl. 38)					0.00504					
					(0.0259)					
Share Intermediate Workers (PCS 4 excl. 47)					-0.0151	-0.0131	-0.0101	-0.0118	-0.0182	-0.0167
					(0.0344)	(0.0344)	(0.0347)	(0.0348)	(0.0377)	(0.0376)
Share Technical Occupations (PCS 38 and 47)					-0.00937	-0.00621	-0.00571	-0.00544	0.00170	0.00169
					(0.0317)	(0.0315)	(0.0314)	(0.0314)	(0.0332)	(0.0332)
Share Engineers (PCS 38)						0.0703**				
						(0.0332)				
Share Technicians (PCS 47)						-0.0585				
						(0.0394)				
Share Non-ICT Engineers (PCS 38 excl. ICT)							-0.00161	-0.000598	-0.0649	-0.0631
							(0.0493)	(0.0492)	(0.0459)	(0.0458)
Share Non-ICT Technicians (PCS 47 Excl. ICT)							-0.0360	-0.0371	-0.0370	-0.0370
							(0.0458)	(0.0458)	(0.0439)	(0.0439)
Share ICT Engineers (ICT of PCS 38)							0.115***		0.159***	
							(0.0439)		(0.0433)	
Share ICT Technicians (ICT of PCS 47)							-0.0949	-0.0967	-0.0333	-0.0269
							(0.0660)	(0.0664)	(0.0791)	(0.0787)
Share ICT Engineers R&D (PCS 388a)								0.0909		0.194***
								(0.0560)		(0.0544)
Share ICT Engineers Admin. & Support (PCS 388b)								0.286**		0.0598
								(0.119)		(0.176)
Share ICT Engineers Manager (PCS 388c)								0.211**		0.100
								(0.0935)		(0.0869)
Share ICT Engineers Sales (PCS 388d)								-0.0608		0.179
								(0.121)		(0.189)
Share ICT Engineers Telecom. (PCS 388e)								-0.190		0.125
								(0.237)		(0.180)
Log Sales	-0.000880	0.00122	0.00122	-0.000344	0.00159	0.000252	0.000415	0.000295	-0.00316	-0.00309
	(0.00771)	(0.00759)	(0.00759)	(0.00758)	(0.00784)	(0.00782)	(0.00790)	(0.00790)	(0.00816)	(0.00815)
Log Age	-0.00425	-0.00456	-0.00495	-0.00470	-0.00473	-0.00409	-0.00377	-0.00347	-0.00198	-0.00198
	(0.00580)	(0.00577)	(0.00576)	(0.00577)	(0.00579)	(0.00578)	(0.00578)	(0.00577)	(0.00966)	(0.00966)
PIK Ratio	-0.00676	-0.00655	-0.00677	-0.00696	-0.00720	-0.00679	-0.00678	-0.00655	-0.00399	-0.00411
	(0.00585)	(0.00585)	(0.00587)	(0.00586)	(0.00590)	(0.00587)	(0.00589)	(0.00587)	(0.00495)	(0.00496)
PKL ratio	-0.00532	-0.00442	-0.00451	-0.00511	-0.00333	-0.00408	-0.00352	-0.00364	-0.00484	-0.00449
	(0.00873)	(0.00864)	(0.00858)	(0.00859)	(0.00886)	(0.00883)	(0.00888)	(0.00888)	(0.00873)	(0.00874)
Log Physical Capital	0.00614	0.00464	0.00497	0.00601	0.00384	0.00450	0.00442	0.00450	0.00995	0.00975
	(0.00897)	(0.00887)	(0.00881)	(0.00883)	(0.00913)	(0.00910)	(0.00914)	(0.00915)	(0.00901)	(0.00901)
Multi-plant	-0.00721	-0.00772	-0.00846	-0.00800	-0.00790	-0.00758	-0.00755	-0.00770	-0.000746	-0.000605
	(0.0113)	(0.0113)	(0.0112)	(0.0113)	(0.0113)	(0.0112)	(0.0112)	(0.0112)	(0.0105)	(0.0105)
Exporter	-0.0291**	-0.0269**	-0.0253**	-0.0272**	-0.0268**	-0.0282**	-0.0279**	-0.0269**	0.00200	0.00182
	(0.0116)	(0.0113)	(0.0115)	(0.0113)	(0.0116)	(0.0116)	(0.0116)	(0.0115)	(0.0114)	(0.0113)
Fast Broadband	0.0331***	0.0350***	0.0353***	0.0338***	0.0349***	0.0336***	0.0335***	0.0329***	0.0306**	0.0313**
	(0.0123)	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0123)	(0.0123)	(0.0123)	(0.0126)	(0.0126)
CRM	0.0393***	0.0406***	0.0404***	0.0394***	0.0405***	0.0402***	0.0399***	0.0396***	0.0328***	0.0326***
	(0.0106)	(0.0106)	(0.0106)	(0.0105)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0107)	(0.0107)
ERP	0.0243**	0.0252**	0.0251**	0.0245**	0.0247**	0.0254**	0.0258**	0.0259**	0.0231**	0.0230**
	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)
E-Commerce	0.00810	0.00688	0.00447	0.00577	0.00754	0.00788	0.00795	0.00839	0.0101	0.0102
	(0.0136)	(0.0136)	(0.0137)	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Observations	7,339	7,339	7,339	7,339	7,339	7,339	7,339	7,339	7,226	7,226
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.044	.044	.044	.044	.043	.045	.046	.048	.048	.048

Table B.1: Estimated margins for Equation B.1. Models from 1 to 8 estimate the equation using variables in 2011, but the dependent, that is relative to year 2018. Models 9 and 10 are estimated using the dependent and shares computed in 2018, whereas controls are in 2011.

IT developments. They typically coordinate studies and work, as well as the IT resources related to the project.

- ICT Engineer, Sales (PCS 388d): Engineers and executives in the private sector responsible for technical and commercial relations with the client base of IT companies: analysing customer needs, sales, and monitoring the implementation of applications or hardware.

- ICT Engineer, Telecommunication (PCS 388e): Engineers and executives in the private sector responsible for negotiating and prescribing solutions in the fields of network computing and telecommunications, organising, and overseeing prescribed IT developments. They typically provide supervision for studies and resources related to the project.