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The role of human capital for AI adoption: Evidence from French firms

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Abstract
We leverage a uniquely comprehensive combination of data sources to explore the enabling role of human capital in fostering the adoption of predictive AI systems in French firms. Using a causal estimation approach, we show that ICT engineers play a key role for AI adoption by firms. Our estimates indicate that raising the current average share of ICT engineers in firms not using AI (1.66%) to the level of AI users (6.7%) would increase their probability to adopt AI by 0.81 percentage points - equivalent to an 8.43 percent growth. However, this would imply substantial investments to fill the existing gap in ICT human capital, amounting to around 450.000 additional ICT engineers. We also explore potential mechanisms, showing that the relevance of ICT engineers for predictive AI is driven by the innovative nature of its use, make-vs-buy choices, large availability of data, ICT and R&D intensity.

Keywords: artificial intelligence, human capital, technological diffusion
JEL codes: J24; O33

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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 to spur innovation and productivity across the economy (Agrawal et al., 2022; Cockburn et al., 2018; Bianchini et al., 2022; Brynjolfsson et al., 2018; Deperi et al., 2023; Noy and Zhang, 2023). 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). Workforce skills explain at least one-third of cross-sector-country differences in AI adoption (Brey and van der Marel, 2024). On the other hand, the rapid diffusion of AI will change the demand for skills (Alekseeva et al., 2021; Squicciarini and Nachtigall, 2021; Borgonovi et al., 2023) and reshape labour markets due to a large exposure of occupations to AI (Webb et al., 2018; Felten et al., 2021, 2023; Brynjolfsson et al., 2018; Eloundou et al., 2023; Brynjolfsson et al., 2023; Engberg et al., 2024) thanks to the high automation potential of AI technologies (Savona et al., 2022; Acemoglu and Restrepo, 2019) and the skill-biased technical change induced by them (Autor, 2024).

Yet, the empirical literature on the relationship between AI and human capital is still limited and mostly focused on how AI impacts labour market outcomes. Evidence on the relationship between employment and AI exposure is mixed: positive in EU sectors (Albanesi et al., 2023), negative in EU regions (Prytkova et al., 2024), and not significant across U.S. occupations and industries (Acemoglu et al., 2022).[1] The demand for AI-related skills at the firm level proxied by data on job postings is higher in firms with greater cash holdings and R&D expenditures (Alekseeva et al., 2021) and in those posting more STEM-related vacancies (Draca et al., 2024). Furthermore, AI skills are often sought in combination with socio-emotional and foundational skills (Borgonovi et al., 2023). Importantly, firm-level AI investments – measured by changes in the share of workers with AI-related skills – have been shown to positively affect the proportion of workers specialised in technical skills (Babina et al., 2023).

The enabling role of human capital in fostering AI adoption remains largely unexplored, primarily due to data constraints which prevent the precise measurement of human capital, particularly at the firm level. This limits the ability to design labour market, skill and education policies to ensure that the productivity-enhancing potential of AI technologies is

[1] Mixed results are common in empirical studies on automation technologies (see also Jin and McElheran, 2018; Aghion et al., 2020; Domini et al., 2021, 2022; Bisio et al., 2023; Ughi and Mina, 2023).

fully exploited. There is evidence at the aggregate level that workforce skills account for at least one-third of the sector-country differences in AI diffusion rates (Brey and van der Marel, 2024). Similarly, ICT skills are linked to AI use by firms in several OECD countries (Calvino and Fontanelli, 2023b,a). Yet, there is no evidence on the role of specific occupations in fostering AI adoption.

We carry out the first analysis of how the quality and type of human capital within firms – captured through a detailed classification of occupations – influences the probability of AI adoption, conditional on other firm's characteristics. We leverage novel and uniquely comprehensive official data sources from France – the ICT survey, linked employer-employee data (LEED), balance-sheets, and the business registry – for a representative sample of approximately 9,000 French firms over the period. The ICT survey provides information on the adoption of AI and other digital technologies by firms in 2018, an early period of diffusion when AI systems were mostly aimed at predictive analytics (e.g., text mining and machine learning). Based on LEED, we explore in detail the role of higher intellectual (e.g., managers, executives, engineers) and intermediate (e.g., supervisors, foremen, technicians) occupations in fostering AI adoption. Higher intellectual occupations are characterised by highly specialised technical knowledge or managerial capabilities requiring in-depth scientific, administrative and commercial knowledge. Intermediate occupations include workers positioned between executives and execution agents. Importantly, within these two macro-classes we further distinguish between human capital related to information and communication technology (ICT), and non-ICT technical and non-technical human capital. These occupational classes broadly reflect the quality and type of human capital of French firms.

We show that the share of ICT engineers has a positive and significant effect on the probability to adopt AI technologies. This result is robust to the use of an instrumental variable approach: raising the current average share of ICT engineers in firms not using AI (1.66%) to the level of AI users (6.7%) would increase their probability to adopt AI by 0.81 percentage points - equivalent to a 8.43 percent growth. Yet, doing so would require almost half a million ICT engineers (about 450.000 FTE jobs). This is roughly equivalent to the size of the current stock of ICT engineers in France. Our estimates thus imply that the current supply of ICT engineers is likely not sufficient to foster the diffusion of AI technologies among French firms. Given current trends, increasing the availability of ICT engineers in France to this level would require more than 15 years.

To further detail some of the mechanisms behind the crucial role played by ICT engineers in the adoption of AI, we carry out three exercises. First, we focus on even more granular classifications of ICT engineering occupations. We show that the AI-human capital link is driven by ICT engineers specialised in R&D. This underscores that advanced ICT human capital is needed to use predictive AI systems due to the importance of R&D capabilities in the ICT domain. Second, we explore differences between firms buying AI from external providers (AI buyers) and those developing their own AI systems (AI developers). We show that both buyers and developers are characterized by higher shares of ICT engineers in the workforce, but that they make a different use of predictive AI systems. Consequently, the link between AI and ICT engineers is stronger for developers, because the ICT competences leveraged by the latter category of users are more diversified. However, non-ICT high-skilled occupations are also positively and significantly linked to the development of AI systems, suggesting that advanced human capital beyond ICT play a relevant role in building domain-specific AI solutions. Third, we study whether the role of ICT engineers differ across sectors. We show that the share of ICT engineers plays a significant role in fostering the adoption of AI in Wholesale & Retail, ICT business services and Professional, Scientific & Technical services, suggesting the relevance of advanced ICT knowledge for applications related to large datasets or involving a high-level of ICT and R&D competences.

The estimates presented in this paper show the strong enabling role that specific human capital plays in the adoption of AI. They thus point to the necessity of significant investments in complementary human capital to foster the diffusion of AI over the next years while at the same time limiting potential shortages in ICT human capital.

The remaining of the paper is organised as follows. Section 2 describes the econometric models. Section 3 describes the data sources used in the analysis carried out in Section 4. Section 5 discusses why ICT engineers are relevant in the context of predictive AI systems. Section 6 summarises the key findings and discusses possible avenues for future research.

2 Empirical Model

Our working hypothesis is that the probability that a firm adopts AI is a function of its human capital endowment and of other relevant firm-specific characteristics. Our empirical model is as follows:

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

where AI User$_i$ is the dummy variable indicating the use of AI by firm i in 2018. Occupation Share$_i$ is a vector characterising the human capital of a given firm based on the share of workers in different. All other co-variates control for potential confounding factors in the relationship between AI use and human capital, as measured by the occupation shares.

Firm characteristics influencing both the probability of adopting AI and the characteristics of a firm's human capital include the size and age of the firm, its endowment of both physical and intangible capital, and specific characteristics such as being multi-plant or export-oriented. Since AI users tend to be larger and younger (Calvino and Fontanelli, 2023b), and these characteristics may also affect the occupational structure of firms, accounting for is required when exploring the role of human capital. 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 accounts for the digital infrastructure internal or external to the firm which represents a pivotal enabler for the adoption of AI technologies, as suggested by recent studies (Calvino and Fontanelli, 2023b; McElheran et al., 2023). On the one hand, a digital infrastructure – such as 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, the availability of meaningful, detailed datasets on productive inputs need to be available to the firm in order for AI to enhance resource efficiency.

Lastly, *industry fixed effects* control for 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. *Regional fixed effects* control for geographic factors, such as the existence of AI hubs across France located in the surrounding of Paris, Lyon, Nice, and Grenoble areas.

Given the binary nature of our dependent variable, we rely on probit estimation and on IV probit when testing the robustness of our results to endogeneity.

3 Data

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).

Administered by INSEE (French statistical office), the 2019 ICT survey features a rotating sample of approximately 9000 French firms operating in the manufacturing, utilities, construction and non-financial market services sectors, with specific questions related to the use of advanced digital technologies in the year 2018.[2] 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 people employed.

Part of the ICT survey is dedicated to questions on AI use by firms. In particular, firms are asked whether they used AI technologies in 2018.[3] It is important to note that 2018 is a period prior to the recent boom in generative AI. Our dependent binary variable, which takes the value of 1 for AI users, thus informs on whether the firm was using AI systems aimed at performing data-driven out-of-sample predictions (e.g., forecasts and classifications). The survey also allows to categorise 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.

The survey also provides useful proxies for the vector of *Digital Controls*. First, we use information on whether the firm's broadband connection speed to build a proxy for the firm's

[2]The survey is administered yearly. Yet, the questions vary year by year, so this - together with the rotating sample nature of the survey - means that our analysis is limited to 2018. Additional details about the survey, known as the "Enquête sur les Technologies de l'Information et de la Communication (TIC)", can be accessed here.

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

digital infrastructure: a binary variable equal to one if fast broadband connection equals or exceeds 100 megabits per second, i.e., the highest speed among the possible available choices. Our hypothesis is that 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. Second, we use information on the use of Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) software, and participation in e-commerce activities as proxies for the existence of an internal digital infrastructure within firms. CRM and e-commerce practices allow the collection of customer and product information; ERP favours the collection of data on productive inputs that can be leveraged to enhance resource efficiency through AI algorithms. Note that 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 (Calvino and Fontanelli, 2023a). Our second source of are French LEED[4], a dataset providing information on the population of French workers. We use employee-level data on hours worked and occupation type, and aggregate these data at the firm level by computing the share FTE workers by occupation classes. Each share is defined as the total number of FTE in an occupation class over the total number of workers in the firm.

Based on the French occupation classification PCS,[5] we consider Higher intellectual occupations (PCS 3) and Intermediate occupations (PCS 4). The former 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, whose tasks are typically difficult to routinise but also mostly exposed to AI (see e.g., Felten et al., 2021). The latter encompasses intermediate positions, between executives and execution agents (e.g., supervisors and foremen), and non-administrative technicians (e.g., appliance repairer, laboratory technicians). We further divide higher intellectual and intermediate occupations into three classes:

- ICT occupations: ICT engineers (PCS 388a, 388b, 388c, 388d and 388e) and ICT technicians (478a, 478b, 478c and 478d)
- Technical non-ICT occupations: non-ICT engineers (PCS 38 excluding 388a, 388b, 388c,

[4]Obtained from the *Déclaration annuelle de données sociales* (DADS). For more information at this link.

[5]For additional details on the PCS classification, version 2003, see 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.

388d and 388e) and non-ICT technicians (PCS 47 excluding 478a, 478b, 478c and 478d)

- Non-technical workers: higher intellectual non-technical workers (PCS 3 excluding 38) and intermediate non-technical workers (PCS 4 excluding 47)

The final classification considered reflects the quality and type of workers' human capital, and is reported in Table 1.[6]

Lastly, firm-level administrative data from balance sheets and the business register [7] provides information related to the set of *Firm Characteristics* on which we condition our estimates, namely the logarithms of firm sales and age, the log of physical to intangible capital ratio, the log of physical capital to total FTE workers, logarithm of physical capital, as well as export and multi-plant status dummies. We build two indexes of capital intensity. First, the firm's physical to intangible capital ratio is defined as the logarithmic difference between physical and intangible capital. Second, the firm's physical capital to employment ratio is computed as the logarithmic difference the physical capital and the total amount of FTE workers. All variables are adjusted using deflators defined based on the A38 sectoral classification and provided by the Banque de France, with the exception of intangible capital, deflated using deflators from the EUKLEMS & INTANProd database (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).

Industry dummies include categories for Accommodation & Food, Administrative, Real Estate, Construction, Media & Telecommunications (NACE 58-61), ICT Business Services (NACE 62-63), Manufacturing, Utilities, Professional & Scientific, Transportation & Storage, and Wholesale & Retail sectors, broadly corresponding to NACE macro sectors. We also provide robustness checks employing 2-digit industry fixed effects, which broadly confirm our results. *Regional dummies* assign each firm to a region within France.

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.

[6]Classes 38 and 47, including engineers and technicians, correspond to the definition of techies used in Harrigan et al. (2021, 2023).

[7]For additional details about these datasets, please refer to this link for balance sheet data (FARE), and this link for the business register.

3.1 Summary statistics

Table 2 shows the summary statistics of our sample. The averages are computed for the entire sample, distinguishing between firms that used AI in 2018 and those that did not.

In 2018, 11.49% of French firms were using AI; 9.99% purchased AI from external sources, 3.21% developed AI in-house. This shows that some firms both bought and developed AI: notably, 53.1% of AI developers were also buyers, while only 17.07% of AI buyers were also developers. This points to a potential relationship between the decisions to buy and develop AI. It also suggests 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.

AI users are on average larger and younger than non-users, in line with existing evidence (Acemoglu et al., 2022; Zolas et al., 2020). Similarly, AI users have more than 4 times the physical capital of non-users. Approximately 34% of AI users export and own multiple plants, while the non-users shares of exporters and multiplant firms is around 30%.

Taken together, the statistics on firm's characteristics confirm the relevance of complementarities: larger firms are more likely characterised by availability or presence of complementary assets (Calvino and Fontanelli, 2023b), including their embedding in the intangible capital and workforce of firms. They also align with the hypothesis 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.

AI users also rely more on digital infrastructure, both within and outside the firm. The share of AI users leveraging fast broadband services (21.55%) is larger than the one of non-users (12.07%); AI users also adopt business digital technologies more frequently than other firms, with rates of usage of CRM, ERP and E-commerce by firms employing AI systems being 42.29%, 57.26% and 17.11% respectively, compared to the 25.95%, 46.93% and 13.71% of other firms employing these technologies. 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 are more likely to have a well-established digital infrastructure, enabling them to collect and organise data.

Focusing on human capital, AI users have a higher share of 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 difference 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 R&D capabilities in the ICT domain.

The summary statistics discussed in this section suggest that, on average, AI users are larger, younger, slightly more intangible and labour intensive, and more digitalised. Furthermore, notwithstanding firm-level shares of workers vary across all occupations considered, AI users leverage ICT human capital to higher extent and particularly in the domain of higher intellectual occupations. However, they may also rely on the lower quality ICT knowledge embedded in other ICT technicians. For this reason, we will focus on the shares of workers belonging to higher intellectual and intermediate occupations.[8]

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 Which occupations spur AI use by firms?

We estimate Equation 1 using a Probit model to shed light on the relationship between AI use and human capital as measured by the occupation classes provided in Table 1 and present the estimated margins in Table 3. We start with a parsimonious model which only includes the human capital proxies and add an increasing number of controls. Only the share of ICT engineers is statistically significant across models, indicating that firms with a higher

[8]Furthermore, we show in Table A.1 that the use of AI is related to higher intellectual occupations only.

share of highly specialised ICT human capital are more likely to use AI, conditional on other confounding factors. The magnitude of the coefficient decreases by roughly two fifths when controls such as industry dummies, firm's size and age, and ICT infrastructure are included. Including further controls on the capital structure of the firm and its multi-plant and export status does not further lower the coefficient, suggesting that the large number of controls we include is sufficient to reduce substantially possible omitted variable biases.

The AI-age relation is not significant and AI-size relation loses its significance when proxies for ICT assets are included in the model, suggesting that these may be mediating factors. The presence of fast broadband and the use of other digital technologies (in particular ERP and CRM) are positively and significantly correlated to the use of AI, pointing to the pivotal role of digital infrastructure and other digital technologies to promote AI use. The coefficients associated with the proxies of intangible assets, labour intensity, export and multi plant status are positive, but not statistically significant.

4.1 Addressing potential endogeneity concerns

Notwithstanding our focus on early phase of diffusion of AI technologies, it is still plausible that AI use by firms may have affected their occupational structure, as suggested by Babina et al. (2023). Furthermore, high-skilled workers are estimated to be the most exposed to AI (e.g. Felten et al., 2021). As a result, the estimated AI-human capital relation may be endogenous and the coefficients estimated in Equation 1 may be biased by the presence of reverse causality. In particular, the coefficient of the probit estimation may be biased upwards: available evidence shows a positive association between AI and high-skill occupations (see e.g. Albanesi et al., 2023), suggesting that AI systems may also spur hirings of ICT engineers. To test the robustness of our results to endogeneity, we rely on an instrumental variable approach. More specifically, we adopt the following IV probit specification:

$$\begin{aligned} \text{AI User}_i^* &= \alpha + \beta_s \widehat{\text{Occupation Share}}_{i,2018} + \beta_{\mathbf{X}} \mathbf{X}_i + \epsilon_i \\ \text{Occupation Share}_{i,2018} &= \gamma + \beta_z \text{Z}_i + \beta_{\mathbf{X}} \mathbf{X}_i + \omega_i \\ \text{AI User}_i &= \begin{cases} 1, & \text{if AI User}_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{2}$$

Where the errors ω_i and ϵ_i follow a bivariate normal distribution. Similarly to the Two Stage Least Square procedure, the IV probit includes two equations (or steps). The first step employs the share of ICT Engineers in 2018 as the dependent variable, that is regressed upon a vector $\mathbf{Z}_i$ of instrumental variables (one for each share of occupations) and $\mathbf{X}_i$, a vector of variables including the same controls of Equation 1 . The second step follows the probit specification of Equation 1: the AI User$_i$ dummy is the dependent variable, which is regressed on the same same vector of controls $\mathbf{X}_i$ of the first step. These two equations are jointly estimated via a Maximum Likelihood estimation procedure, allowing the use of sampling weights.

Given the historical development of AI technologies, we use the 2011 firm-level shares of the different occupational classes as the instrumental variables for the 2018 shares. Our reasoning is as follows: although we do not have information on the year in which each firm adopted the AI technology it was using in 2018, it is well known that until 2011 the development of AI was very limited. 2012 represented a turning point, with many major advancements in AI systems taking place, including for instance the development of the AlexNet neural network (Babina et al., 2021; Engberg et al., 2024). The following 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. Consequently, the surge in AI adoption by firms started after 2011 in the United States. While the United States often lead in early technology adoption, the diffusion of AI technologies in other countries, including France, may have followed with some time lag.

Based on this reasoning, we argue that the 2011 firm-level shares of the different occupational classes is a good IV candidate. Instruments must strongly predict the endogenous variable and at the same time be exogenous, given other controls. First, using the 2011 shares implies that we instrument an endogenous variable with its past value, which, by construction, should be a good predictor. Second, using the 2011 as instrument together with a large set of control variables allows to address two sources of endogeneity that may possibly affect the instrumental variables considered: reverse causality and the presence of relations between AI and other ICT. On the one hand, the instruments considered are not affected by reverse causality, because computed in 2011 when AI use by firms was highly unlikely, especially in France. On the other hand, the set of controls measuring – directly or indirectly – the use of other digital technologies addresses the concern that firms with high shares of ICT workers in 2011 already had complementary assets (such as large datasets) and used other digital technologies. If this was not the case, our instrument would not be completely exogenous. Therefore, the presence of size among controls in the IV specification helps further mitigate possible endogeneity sources to the extent to which ICT adoption is more likely in larger firms (Calvino and Fontanelli, 2023b; McElheran et al., 2023; Cirillo et al., 2023); the inclusion of the capital structure (embedding both tangible and intangible capital) controls for the presence and intensity in the use of other digital technologies. Similarly, the use of CRM, ERP and E-commerce variables accounts for the relation between AI and other digital technologies, that may be otherwise be captured by the presence ICT occupations relations with AI. As already noted, the presence of a fast broadband connection is related to the use of cloud (see DeStefano et al., 2018; Caldarola and Fontanelli, 2024), which is a key technology for the use of AI (Calvino and Fontanelli, 2023b). Finally, regional dummies control for the presence of technological hubs and for other region-specific confounders (e.g. broadband connection quality and speed).

In addition to using the IV probit strategy, we also estimate TSLS specifications. This exercise allows us to also overidentify the exclusion restriction by decomposing the share of ICT engineers in its possible specialisation. The Hansen's tests are not rejected, suggesting that our instruments are indeed exogenous.

Table 4 shows the results of the estimation of Equations 2: the six first stages coefficients of the IV probit and its second stage marginal effects, and the probit equivalent estimations computed on the sample of firms which were alive in 2011. The first stage estimation results indicate that, as expected, the instrumental variables considered are all positively and significantly linked with their respective share of occupations across regressions. The estimation results of the second step of the IV probit equation confirms the results from Section 4, suggesting that higher shares of ICT engineers have a positive impact on the probability to adopt AI. Also, the comparison across the results of the standard probit with the ones of IV probit specifications indicate the presence of a negligible positive bias affecting the coefficient of the main explanatory variable. The IV probit coefficients estimates are lower than the probit ones, confirming the expectation of a positive association between AI and occupations (see e.g. Albanesi et al., 2023).

We report a robustness analysis based on TSLS specifications in Tables A.2 and A.3, Appendix A. We estimate the model with same industry fixed effects as the probit/IV probit specifications, but also using 2-digit industry ones. We also overidentify the exclusion restriction variables by instrumenting the 2018 share of ICT engineers with the 2011 shares of specialised ICT engineers. Overall, the TSLS models confirm the results from the IV probit specifications reported in Table 4. Furthermore, F-statistics estimates are all high and beyond 20, suggesting that the chosen instruments are strong. Finally, the Hansen's tests obtained using the specialised ICT engineering share as instrumental variables indicate that the null hypothesis of instrument exogeneity cannot be rejected, suggesting that our instruments are valid.

4.2 Discussion

Supporting the diffusion of AI technologies among firms is an important policy goal (Calvino and Criscuolo, 2022), on the ground that AI can bring large productivity gains to the economy. The results we present in this paper show a positive, significant and causal relation between highly specialized segments of the workforce (ICT engineers) and the probability to use predictive AI systems. This finding is in line with the predictions emerging from the literature on skill-biased technological change: the ICT human capital relevant for AI is related to engineers and not to technicians or other occupation categories (see Table A.1 in Appendix A). Hence, highly skilled segments of the workforce are at the basis of AI use, consistently with theories of skill-biased technical change (Autor et al., 2003, 1998; Machin and Reenen, 1998). Hence, digital capabilities embedded in IT workers will play a crucial role for the diffusion of AI among firms, in line with discussions in Brynjolfsson et al. (2021). In this respect, the findings of the literature showing that high-skilled workers are more exposed to AI (e.g., Webb, 2020; Felten et al., 2021) may be capturing complementary characteristics between high-skilled workers and AI rather than substitutability between the two, at least as far as predictive AI is concerned.

The magnitude of the enabling effect of ICT engineers on the probability of adopting AI can be quantified as follows: the probability of using AI for non-users would grow by an average of 10.56 percent based on Model 5 of Table 3 - or 8.43 percent if the results of the IV Probit model in Table 4 are used - if the average share of ICT engineers in firms not using AI were to increase to the average level of AI users. This is equivalent to an increase by 1.02 and

0.81 percentage points in the probability to adopt AI for non-users, respectively.[9]

Achieving this 10 percent increase in the probability of adoption by non-user would require increasing the average share of ICT engineers employed in firms not using AI by approximately 5 percentage points - from 1.66 to 6.6 percent (see Table 2). Note that such an increase in the share of ICT engineers for non-users implied a massive increase in the number of ICT engineers: 463,141 new FTE. This is approximately 2.5 times the number of ICT engineers employed in 2018 by firms with at least 10 employees (199,722 FTE) and equivalent to the current stock of ICT engineers in France (433,965 FTE).

Given the crucial role that human capital, and ICT engineers in particular, play in the adoption of AI, this call for large investments. Indeed doubling the current stock of ICT engineers in France at the current pace of increase (on average 4.5% per year between 2010 and 2021, 4.62% between 2010 and 2019) will take between 16 and 17 years.

Our results offer novel evidence of the importance of high level human capital in promoting the adoption of AI among firms. Yet, they may arguably still underestimate the true number of ICT engineers needed to boost AI diffusion among firms: our analysis is based on an early period of AI adoption, where the supply of ICT engineers was highly unlikely to meet demand. That means that the observed share of ICT engineers in firms using AI was likely lower than what would have been actually optimal to efficiently adopt the technology. Furthermore, our sample does not include firms with less than 10 persons employed, which are less likely to employ ICT engineers than larger firms. If this were the case, our estimate would represent a lower bound: an even larger number of ICT engineers will be likely necessary to foster the diffusion of predictive AI systems.

Having said this, we also note that AI technologies are advancing at a very fast pace; for this reason, our predictions represent only short-to-medium term estimates. In the longer term, as predictive AI systems and tools will reach maturity and become more easily available, the specific role of ICT engineers may decrease. If this were the case, ICT engineers currently hired by AI users may partly spread to other firms, allowing a broader diffusion of

[9] We estimate these numbers according to the following procedure. First, we estimate the marginal effect of the share of ICT engineers at the firm level ($\phi(\beta' X)\beta_{\text{ICT Eng.}}$). Second, we compute the firm-level increase in percentage points as the product of the marginal effect and the difference between the average share of ICT engineers of AI users (on average 6.7%) and the actual one of non-users (on average 1.66%). Averaging these firm-level estimates across non-users, we obtain the average percentage point increase reported above and equal to 1.02 percent according to the Probit and 0.81 percent to the IV Probit. Third, we estimate the firm-level growth rate in the probability to use AI as the average of the ratio of the increase in percentage points and the predicted probability to use AI from Probit or IV Probit models ($\Phi(\beta' X)$), and average it across firms to obtain the estimated growth rate in the probability to use AI reported above (10.56% for the Probit or 8.43% for the IV Probit model).

AI technologies into the economy.

5 Why are ICT engineers relevant for the use of AI

In this section, we enrich our findings along three dimensions. First, we explore whether the relation between AI and ICT human capital is driven by a specific profile within ICT engineers. This allows us to test whether any specific ICT profile plays the more relevant role in AI adoption. Indeed, ICT engineers encompass a large number of specialised occupations, characterised by very heterogeneous competences: they can be specialised in R&D, managerial capabilities, telecommunications, sales and customer support (see Section B in the Appendix). Second, we examine how the relationship between AI use and human capital varies depending on whether the firm is an AI buyer, an AI developer, or both. This exercise is motivated by recent empirical evidence showing that AI buyers and adopters are profoundly different (Calvino and Fontanelli, 2023a). Third, we test whether the relationship between ICT human capital and AI adoption is heterogenous across sectors. This is warranted on the basis that not all sectors are equally exposed to digital technologies, including AI (see e.g. Felten et al., 2021).

Specialised ICT occupations - Leveraging on the most detailed occupation classes in our database (4-digit level of the PCS), we explore the link between the probability of adopting AI and specific ICT engineers profiles. These classes encompass very specific occupations related to various ICT-related human capital.[10] As shown in Table 5, the coefficient associated to ICT engineers specialised in R&D is positive and significant. This points to the crucial role of R&D capabilities within the broader category of ICT engineers. Such capabilities are critical for AI use. This result is also in line with the findings of Alekseeva et al. (2021), which shows a positive relation between AI use and R&D investments, by highlighting that R&D competences in the ICT domain are particularly relevant. Indeed, the presence of ICT engineers specialised in R&D is an indication that the firm likely engages in innovation efforts in the ICT domain

[10]We describe these classes in Section B of the Appendix.

AI buyers and AI developers - Recalling that AI users can source AI differently, we estimate the following biprobit model to investigate differences in the enabling role of ICT human capital between AI buyers and AI developers :

$$\text{AI Buyer}_i = \begin{cases} 1 & \text{if } \beta_1 X_i + \varepsilon_{i,1} > 0, \\ 0 & \text{otherwise,} \end{cases}, \quad \text{AI Developer}_i = \begin{cases} 1 & \text{if } \beta_2 X_i + \varepsilon_{i,2} > 0, \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$
$$\textbf{Corr}(\varepsilon_{i,1};\ \varepsilon_{i,2}) = \rho$$

X_i is the vector of firm-level characteristics including including Occupation 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, namely the decisions to buy and/or develop in-house AI systems. This is achieved by modelling the correlation between the error terms of the two equations. In our case, it is relevant to control for such unobservables because make-or-buy AI decisions appear to be positively correlated (see the discussion in Section 3.1).

Table 6 shows the results of both the baseline occupation shares (Model 1) and the version with specialised ICT engineers (Model 2). The coefficients associated with the share of ICT engineers is positive and significant for both AI buyers and developers (Model 1), confirming results discussed in Section 4. However, the relation estimated for the former is weaker both in magnitude and significance, suggesting that developers more strongly rely on advanced ICT human capital. Moreover, R&D engineers are crucial for both AI buyers and developers (Model 2), but other specialised ICT engineering occupations play an enabling role in firms developing in-house their own AI systems. This points to a more diversified use of advanced ICT capabilities and to differences in the use of AI by firms with different profiles.

Three specific results are worth highlighting. First, the share of ICT engineers specialised in sales is significantly higher in AI developers, suggesting that they may sell AI-related products or services to other firms. Furthermore, even though all AI users are significantly linked to CRM software, developers show a stronger correlation. This suggests that AI developers may focus more on AI-related product innovations. Instead, only buyers associated with ERP software. This indicates that AI buyers may integrate AI tools to provide predictions based on multiple data sources of firms and assist therefore managerial decision-making, thereby focusing more on AI-related process innovations. Conversely, AI developers already rely on in-depth administrative and commercial non-ICT knowledge (i.e., the share of non-technical higher intellectual occupations). Second, the presence of fast broadband is positively and significantly linked to AI buyers only. This indicates that firms buying AI from external sources may run their AI models on external platforms thanks to cloud technologies. Conversely, the significance of telecommunications and computer networks engineers (see also Igna and Venturini, 2023) among developers suggests the presence of an internal digital infrastructure for managing data flows and may further explaining why developers may not need the presence a fast broadband.[11] Third, AI developers also leverage ICT managers, due to the fact that in-house development of AI technologies is linked to complex organisational changes that may be more easily accomplished by relying on specialised coordinators. Lastly, the coefficient associated with the share of non-ICT engineers and non-technical higher intellectual occupations is positive and significant for AI developers. This suggests that presence of cross-disciplinary domain knowledge embedded in advanced technical and non-technical human capital beyond ICT plays an important role in designing AI solutions for specific functions.

Heterogeneity across sectors - Finally, we estimate Equation 1 on sample of firms belonging to six different sectors: Manufacturing (NACE 10-33), Wholesale & Retail (NACE 45-47), Media & Telecommunications (NACE 58-61, 951), ICT Business Services (NACE 62-63), Professional, Scientific And Technical Services (NACE 69-75), and Other Services (NACE 49-56, 68, 77-82).[12]

Table 7 reveals large heterogeneity across sectors. The positive and significant relationship between AI use and the share of ICT engineers is confirmed for three sectors, namely Wholesale & Retail, ICT Business service and Professional, Scientific and Technical service sectors. This suggests that the need for advanced ICT knowledge is primarily driven by firms managing large dataset or using AI for complex applications requiring significant ICT or R&D intensities. 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, probably for selling AI-related solutions to cus-

[11]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.

[12]This aggregation aims to capture commonalities between more disaggregate sectors to ensure a representative number of AI users is included relative to sectoral numerosity, and at the same time distinguishing those characterised by key elements driving (or hindering) the diffusion of AI. We will not report results for firms belonging to utilities (NACE 35-39) and construction (NACE 41-43) due to the limited number of observations/AI users in these sectors.

tomers. Furthermore, the share of ICT technicians in Other Services is significant, revealing that predictive AI systems are likely less complex in these sectors than in ones where ICT engineers are relevant. Lastly, in the Manufacturing sector, AI users significantly and positively leverage technical non-ICT workers, possibly suggesting that AI systems in Manufacturing are likely mostly embedded in physical machines.

6 Concluding remarks

We leverage novel and uniquely comprehensive firm-level data sources from France – the ICT survey, linked employer-employee data (LEED), balance-sheets, and the business registry – to provide a more nuanced understanding of how the quality and type of human capital within firms – captured through a detailed classification of occupations – influences the probability of AI adoption, conditional on other firm's characteristics. Our representative sample includes approximately 9,000 French firms over the period.

We show that advanced ICT human capital has a positive and significant effect on the probability that non-users adopt AI. This result is robust to the use of an instrumental variable approach. To further detail some of the mechanisms behind the crucial role played by ICT engineers in the adoption of AI, we carry out three exercises. First, we stress the role of ICT engineers specialised in R&D (i.e., advanced ICT human capital) by leveraging information on even more granular classifications of ICT engineering occupations. Second, we show that both AI buyers and AI developers are characterized by higher shares of ICT engineers in the workforce, but that they make a different use of predictive AI systems. In particular, the link between AI and ICT engineers is stronger for developers, because the ICT competences leveraged by the latter category of users are more diversified. Third, we show that ICT engineers play a significant role in fostering the adoption of AI in Wholesale & Retail, ICT business services and Professional, Scientific & Technical services, suggesting the relevance of advanced ICT knowledge for applications related to large datasets or involving high-levels of ICT and R&D competences.

While broadly consistent with the insights offered by Babina et al. (2023) on the United States, in particular regarding the relevance of highly-educated and STEM workers for AI use, our results expands the existing literature in several directions. First, we extend the analysis of highly representative official data sources beyond the United States. Second, we characterize the occupational structure of AI users, hence the quality and type of human capital which is relevant for firms that want to adopt AI technologies. In particular, our results point to ICT engineers as the crucial profession to increase the average probability of adopting AI. This points to the role of advanced ICT human capital in fostering the diffusion of AI technologies.

The policy relevance of our contribution lies in pointing to the crucial role played by highly qualified technical human capital in the diffusion of AI technologies. If supporting the uptake of such technologies is a relevant policy goal, significant investments in complementary human capital will need to be secured to avoid shortages in ICT human capital.

Several important extensions of this work remain to be explored in future research efforts as more and better data becomes available. As AI diffuses more broadly into our economies, it will be crucial to further disentangle the role of human capital as a pre-requisite for AI use from changes in occupational composition and organisational structure resulting from the deployment of AI systems. Furthermore, similar analyses should be extended to other countries, further nuancing the understanding of the complementarities between human capital, AI, and other digital technologies (see also Dell'Acqua et al., 2023). The complementarity of different human capital within each firm, depending on the type of AI application, should also be explored to strengthen and further nuance our results which indicate that the development of AI systems leverages technical and non-technical human capital beyond the ICT domain. Finally the present analysis should be extended to explore the extent to which human capital is instrumental in realising the productivity potential of AI.

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	ICT	Technical non-ICT	Non-technical human capital
Higher intellectual occupations	ICT engineers	Non-ICT engineers	Non-technical (e.g., executives)
Intermediate occupations	ICT technicians	Non-ICT technicians	Non-technical (e.g., supervisors)

Table 1: The main human capital classification used in the analysis. We report the level in blue and and the type in red.

Summary Statistics

	All	Other Firms	AI Users
AI Users	11.49%		
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
Physical to Intangible Capital Ratio	4.56	4.59	4.39
Physical Capital to Employment 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 2: 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.

The AI-human capital relation

	Model 1	Model 2	Model 3	Model 4	Model 5
ICT Engineers	0.257***	0.209***	0.187***	0.165***	0.165***
	(0.0287)	(0.0404)	(0.0411)	(0.0412)	(0.0414)
Non-ICT Engineers	0.0419	0.0362	0.0131	-0.00423	-0.00798
	(0.0412)	(0.0410)	(0.0427)	(0.0425)	(0.0430)
Non-technical Higher Intellectual	0.107***	0.0675**	0.0509	0.0221	0.0221
	(0.0251)	(0.0310)	(0.0321)	(0.0320)	(0.0333)
ICT Technicians	0.0376	-0.00265	-0.00695	-0.0496	-0.0501
	(0.0660)	(0.0741)	(0.0748)	(0.0755)	(0.0750)
Non-ICT Technicians	-0.00290	-0.00434	-0.0120	-0.0180	-0.0179
	(0.0412)	(0.0415)	(0.0421)	(0.0426)	(0.0429)
Non-technical Intermediate	0.0255	0.0150	0.00927	0.000734	0.00205
	(0.0276)	(0.0282)	(0.0289)	(0.0293)	(0.0296)
Log Sales			0.00952***	0.00239	-0.00298
			(0.00308)	(0.00339)	(0.00692)
Log Age			-0.00935	-0.00811	-0.0105
			(0.00645)	(0.00637)	(0.00670)
Fast Broadband				0.0279**	0.0273**
				(0.0119)	(0.0119)
CRM				0.0412***	0.0398***
				(0.00986)	(0.00988)
ERP				0.0211**	0.0209**
				(0.0102)	(0.0102)
E-commerce				0.0106	0.00931
				(0.0123)	(0.0124)
Physical to Intangible Capital Ratio					-0.00429
					(0.00421)
Physical Capital to Employment Ratio					-0.00330
					(0.00761)
Log Physical Capital					0.00674
					(0.00783)
Multi Plant					0.00188
					(0.00973)
Exporter					0.00552
					(0.0107)
Observations	8,530	8,530	8,530	8,530	8,530
Industry FE	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes
Pseudo R2	.025	.035	.037	.047	.048

Table 3: Estimated marginal effects of Equation 1.

The effect of human capital on the adoption of AI systems

	Probit	IV Probit						
		Second Stage	First Stages					
	Margins	Margins	ICT Engineers	Non-ICT Engineers	Non-Technical Higher Intellectual Occ.	ICT Technicians	Non-ICT Technicians	Non-Technical Intermediate Occ.
ICT Engineers (2018)	0.152***	0.130**						
	(0.045)	(0.062)						
Non-ICT Engineers (2018)	-0.061	0.004						
	(0.045)	(0.076)						
Non-technical Higher Intellectual (2018)	-0.021	-0.065						
	(0.037)	(0.057)						
ICT Technicians (2018)	-0.044	-0.086						
	(0.081)	(0.072)						
Non-ICT Technicians (2018)	-0.046	-0.165						
	(0.044)	(0.108)						
Non-technical Intermediate (2018)	-0.001	-0.015						
	(0.032)	(0.048)						
ICT Engineers (2011)			0.750***	0.060***	0.010	0.004	-0.053**	-0.048***
			(0.044)	(0.020)	(0.015)	(0.014)	(0.025)	(0.016)
Non-ICT Engineers (2011)			-0.008	0.697***	0.107***	-0.007	0.022	0.005
			(0.008)	(0.040)	(0.028)	(0.006)	(0.033)	(0.023)
Non-technical Higher Intellectual (2011)			-0.005	0.110***	0.693***	0.025***	-0.073***	-0.019
			(0.004)	(0.019)	(0.038)	(0.009)	(0.013)	(0.014)
ICT Technicians (2011)			0.018	0.043**	0.027	0.643***	-0.031	0.006
			(0.035)	(0.021)	(0.018)	(0.059)	(0.023)	(0.024)
Non-ICT Technicians (2011)			0.026**	0.027**	0.001	-0.003	0.600***	0.056***
			(0.012)	(0.014)	(0.013)	(0.005)	(0.027)	(0.020)
Non-technical Intermediate (2011)			-0.002	-0.004	0.010	0.001	0.070***	0.664***
			(0.003)	(0.007)	(0.006)	(0.003)	(0.012)	(0.022)
Log Sales	-0.003	-0.002	-0.001	0.004*	-0.003	-0.002***	0.016***	0.009***
	(0.008)	(0.008)	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)
Log Age	-0.002	-0.001	-0.006***	-0.004	0.002	-0.001	0.008**	0.002
	(0.009)	(0.009)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.004)
Fast Broadband	0.029**	0.031**	0.004	0.003	0.003	0.002	0.015**	-0.005
	(0.012)	(0.013)	(0.003)	(0.005)	(0.004)	(0.003)	(0.006)	(0.006)
CRM	0.033***	0.034***	-0.001	0.001	-0.002	0.003	0.008**	0.010**
	(0.011)	(0.011)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
ERP	0.020*	0.022**	0.001	0.001	0.003	0.003**	0.008**	0.000
	(0.011)	(0.011)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)
E-commerce	0.011	0.011	-0.003*	-0.007***	-0.004*	-0.002	-0.002	0.005
	(0.013)	(0.013)	(0.001)	(0.002)	(0.002)	(0.001)	(0.004)	(0.005)
Physical to Intangible Capital Ratio	-0.005	-0.005	-0.001	-0.002	0.002	0.000	-0.002	-0.002
	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Physical Capital to Employment Ratio	-0.005	-0.004	-0.005**	0.005*	-0.004	-0.001	0.016***	0.007**
	(0.009)	(0.009)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)
Log Physical Capital	0.009	0.008	0.004*	-0.001	0.005	0.001	-0.019***	-0.011***
	(0.009)	(0.009)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)
Multi Plant	-0.001	-0.001	-0.004**	-0.003	0.003	-0.001	-0.001	0.012***
	(0.010)	(0.010)	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)
Exporter	0.000	0.000	0.001	0.011***	-0.003	-0.000	0.009**	-0.008*
	(0.011)	(0.012)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Observations	7,379	7,379	7,379	7,379	7,379	7,379	7,379	7,379

Table 4: Estimation results of Equation 2, when also the other 2018 shares of PCS occupations are instrumented with their 2011 value. Margins, estimates of the second stage and of the six different first stages (one for each occupation share) are reported.

AI Users and Specialised Engineers	
R&D ICT Engineers	0.182***
	(0.0497)
Admin. & Support ICT Engineers	0.0170
	(0.166)
ICT Managers	0.137
	(0.0856)
Sales ICT Engineers	0.221
	(0.147)
Telecomm. ICT Engineers	0.225
	(0.173)
Non-ICT Engineers	-0.00642
	(0.0429)
Non-Technical Higher Intellectual	0.0231
	(0.0332)
ICT Technicians	-0.0443
	(0.0748)
Non-ICT Technicians	-0.0186
	(0.0429)
Non-Technical Intermediate	0.00188
	(0.0296)
Log Sales	-0.00308
	(0.00691)
Log Age	-0.0105
	(0.00670)
Fast Broadband	0.0277**
	(0.0119)
CRM	0.0399***
	(0.00988)
ERP	0.0209**
	(0.0102)
E-commerce	0.00945
	(0.0124)
Physical to Intangible Capital Ratio	-0.00442
	(0.00422)
Physical Capital to Employment Ratio	-0.00329
	(0.00761)
Log Physical Capital	0.00682
	(0.00782)
Multi Plant	0.00187
	(0.00973)
Exporter	0.00562
	(0.0107)
Observations	8,530
Industry + Region FE + Additional controls	Yes
Pseudo R2	.048

Table 5: Estimated margins for Equation 1, when ICT engineers are disaggregated into specialised occupations.

AI Buyers and Developers				
	Model 1		Model 2	
	AI Buyer	AI Developer	AI Buyer	AI Developer
ICT engineers	0.0717*	0.0834***		
	(0.0374)	(0.0163)		
R&D ICT Engineers			0.0756*	0.0868***
			(0.0447)	(0.0183)
Admin. & Support ICT Engineers			-0.00217	0.0581
			(0.187)	(0.0570)
ICT Managers			0.123	0.0557*
			(0.0854)	(0.0312)
Sales ICT Engineers			-0.160	0.128***
			(0.135)	(0.0483)
Telecomm. ICT Engineers			0.258	0.149**
			(0.180)	(0.0586)
Non-ICT Engineers	-0.0725	0.0419***	-0.0737	0.0428***
	(0.0466)	(0.0159)	(0.0469)	(0.0158)
Non-technical higher intellectual	-0.00144	0.0350**	-0.000957	0.0353**
	(0.0310)	(0.0144)	(0.0310)	(0.0144)
ICT technicians	-0.0653	0.0147	-0.0637	0.0154
	(0.0818)	(0.0216)	(0.0824)	(0.0216)
Non-ICT technicians	-0.0247	0.0284	-0.0237	0.0279
	(0.0416)	(0.0183)	(0.0415)	(0.0184)
Non technical intermediate	-0.00300	0.00157	-0.00341	0.00174
	(0.0282)	(0.0148)	(0.0281)	(0.0147)
Log Sales	-0.000141	-0.000919	-9.17e-05	-0.00105
	(0.00661)	(0.00306)	(0.00661)	(0.00305)
Log Age	-0.00594	-0.0108***	-0.00619	-0.0106***
	(0.00649)	(0.00294)	(0.00650)	(0.00295)
Fast Broadband	0.0261**	0.00673	0.0262**	0.00695
	(0.0114)	(0.00511)	(0.0114)	(0.00511)
CRM	0.0303***	0.0241***	0.0308***	0.0239***
	(0.00955)	(0.00465)	(0.00953)	(0.00465)
ERP	0.0196**	0.00231	0.0199**	0.00216
	(0.00975)	(0.00453)	(0.00974)	(0.00452)
E commerce	0.00402	0.00808	0.00394	0.00833
	(0.0119)	(0.00527)	(0.0119)	(0.00528)
Physical to Intangible Capital Ratio	-0.00439	-0.00220	-0.00472	-0.00211
	(0.00400)	(0.00185)	(0.00401)	(0.00185)
Physical Capital to Employment Ratio	0.00405	-0.00501	0.00434	-0.00528
	(0.00714)	(0.00369)	(0.00714)	(0.00370)
Log Physical Capital	0.000381	0.00656*	0.000241	0.00668*
	(0.00739)	(0.00368)	(0.00739)	(0.00368)
Multi Plant	-0.00227	0.00722	-0.00224	0.00739
	(0.00933)	(0.00452)	(0.00932)	(0.00451)
Exporter	0.00263	8.86e-05	0.00274	8.18e-05
	(0.0103)	(0.00484)	(0.0103)	(0.00484)
Observations	8,531	8,531	8,531	8,531
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Table 6: Estimated margins for Equation 3, also when ICT engineers are disaggregated into specialised occupations.

Sectoral regressions

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

Table 7: Estimated margins for Equation 1 for different sectors.

A Additional tables

	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	0.0734***	0.0526**	-0.0160	-0.0238	-0.0106	-0.00775	-0.0184	-0.00364
	(0.0239)	(0.0246)	(0.0236)	(0.0239)	(0.0195)	(0.0197)	(0.0190)	(0.0194)
Log Sales	0.00923***	-0.00404	0.0124***	-0.000928	0.0120***	-0.00158	0.0117***	-0.00165
	(0.00307)	(0.00686)	(0.00295)	(0.00675)	(0.00297)	(0.00677)	(0.00297)	(0.00683)
Log Age	-0.0108*	-0.0116*	-0.0119*	-0.0124*	-0.0120*	-0.0126*	-0.0117*	-0.0125*
	(0.00644)	(0.00670)	(0.00645)	(0.00669)	(0.00645)	(0.00668)	(0.00646)	(0.00670)
Fast Broadband		0.0275**		0.0307**		0.0301**		0.0301**
		(0.0120)		(0.0120)		(0.0120)		(0.0120)
CRM		0.0397***		0.0417***		0.0413***		0.0411***
		(0.00989)		(0.00987)		(0.00985)		(0.00985)
ERP		0.0193*		0.0210**		0.0204**		0.0206**
		(0.0102)		(0.0103)		(0.0102)		(0.0102)
E commerce		0.00923		0.00720		0.00836		0.00714
		(0.0124)		(0.0124)		(0.0125)		(0.0125)
Physical to Intangible Capital Ratio		-0.00395		-0.00444		-0.00434		-0.00435
		(0.00420)		(0.00419)		(0.00419)		(0.00421)
Physical Capital to Employment Ratio		-0.00560		-0.00382		-0.00403		-0.00421
		(0.00755)		(0.00746)		(0.00748)		(0.00752)
Log Physical Capital		0.00843		0.00640		0.00681		0.00703
		(0.00775)		(0.00770)		(0.00770)		(0.00777)
Multi plant		0.00108		6.82e-05		0.000134		-0.000268
		(0.00978)		(0.00980)		(0.00979)		(0.00982)
Exporter		0.00375		0.00736		0.00686		0.00747
		(0.0108)		(0.0106)		(0.0106)		(0.0106)
Observations	8,530	8,530	8,530	8,530	8,530	8,530	8,530	8,530
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.034	.044	.032	.044	.032	.043	.032	.043

Table A.1: Estimated margins for Equation 1, when 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.

	2nd Stage		First Stage											
			Model 1						c Model 2					
	Model 1	Model 2	ICT Eng.	Non-ICT Eng.	Non-tech. Hig. Int.	ICT Tech.	Non-ICT Tech.	Non-Tech. Int.	ICT Eng.	Non-ICT Eng.	Non-tech. Hig. Int.	ICT Tech.	Non-ICT Tech.	Non-Tech. Int.
ICT Engineers (2018)	0.260^{**}	0.277^{**}												
	(0.107)	(0.125)												
Non-ICT Engineers (2018)	-0.006	0.077												
	(0.087)	(0.106)												
Non-technical Higher Intellectual (2018)	-0.070	-0.075												
	(0.066)	(0.070)												
ICT Technicians (2018)	-0.224^{*}	-0.204												
	(0.120)	(0.128)												
Non-ICT Technicians (2018)	-0.092	-0.038												
	(0.067)	(0.077)												
Non-technical Intermediate (2018)	-0.019	-0.046												
	(0.047)	(0.053)												
ICT Engineers (2011)			0.711^{***}	0.036	-0.041	-0.007	-0.004	-0.013	0.750^{***}	0.060^{***}	-0.053^{**}	0.004	0.010	-0.048^{***}
			(0.048)	(0.025)	(0.027)	(0.017)	(0.017)	(0.018)	(0.045)	(0.020)	(0.025)	(0.014)	(0.015)	(0.016)
Non-ICT Engineers (2011)			-0.003	0.597^{***}	0.093^{***}	0.000	0.021	0.046^{*}	-0.008	0.697^{***}	0.022	-0.007	0.107^{***}	0.005
			(0.009)	(0.041)	(0.035)	(0.007)	(0.028)	(0.025)	(0.008)	(0.040)	(0.033)	(0.006)	(0.028)	(0.023)
Non-technical Higher Intellectual (2011)			0.015	0.040^{***}	0.571^{***}	-0.008	0.012	0.059^{***}	0.026^{**}	0.027^{**}	0.600^{***}	-0.003	0.001	0.056^{***}
			(0.011)	(0.014)	(0.027)	(0.006)	(0.012)	(0.022)	(0.012)	(0.014)	(0.027)	(0.005)	(0.013)	(0.020)
ICT Technicians (2011)			-0.004	0.012	-0.010	0.638^{***}	-0.008	0.035	0.018	0.043^{**}	-0.031	0.643^{***}	0.027	0.006
			(0.036)	(0.021)	(0.026)	(0.059)	(0.019)	(0.024)	(0.035)	(0.021)	(0.023)	(0.060)	(0.018)	(0.024)
Non-ICT Technicians (2011)			-0.005	0.032^{*}	-0.020	0.033^{***}	0.611^{***}	0.021	-0.005	0.110^{***}	-0.073^{***}	0.025^{***}	0.693^{***}	-0.019
			(0.005)	(0.019)	(0.013)	(0.012)	(0.039)	(0.015)	(0.004)	(0.019)	(0.013)	(0.010)	(0.038)	(0.014)
Non-technical Intermediate (2011)			0.001	0.007	0.059^{***}	0.001	0.019^{***}	0.635^{***}	-0.002	-0.004	0.070^{***}	0.001	0.010	0.664^{***}
			(0.003)	(0.006)	(0.013)	(0.003)	(0.006)	(0.022)	(0.003)	(0.007)	(0.012)	(0.003)	(0.006)	(0.022)
Log Sales	-0.003	-0.004	-0.001	0.007^{***}	0.015^{***}	-0.002^{**}	-0.003	0.009^{***}	-0.001	0.004^{*}	0.016^{***}	-0.002^{***}	-0.003	0.009^{***}
	(0.008)	(0.009)	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.001)	(0.003)	(0.003)
Log Age	-0.003	-0.005	-0.005^{***}	-0.001	0.005	-0.001	0.004	0.001	-0.006^{***}	-0.004	0.008^{**}	-0.001	0.002	0.002
	(0.010)	(0.010)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.002)	(0.004)
Fast Broadband	0.039^{**}	0.036^{**}	0.006^{*}	0.005	0.013^{**}	0.003	0.004	-0.009	0.004	0.003	0.015^{**}	0.002	0.003	-0.005
	(0.016)	(0.016)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.006)	(0.003)	(0.004)	(0.006)
CRM	0.039^{***}	0.039^{***}	-0.002	0.003	0.006	0.002	-0.001	0.011^{**}	-0.001	0.001	0.008^{**}	0.003	-0.002	0.010^{**}
	(0.012)	(0.012)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)
ERP	0.021^{*}	0.022^{*}	0.000	0.003	0.005	0.002^{*}	0.004	0.003	0.001	0.001	0.008^{**}	0.003^{**}	0.003	0.000
	(0.011)	(0.011)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)
E-commerce	0.011	0.010	-0.004^{**}	-0.008^{***}	-0.002	-0.002	-0.004^{*}	0.001	-0.003^{*}	-0.007^{***}	-0.002	-0.002	-0.004^{*}	0.005
	(0.015)	(0.016)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.006)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)	(0.005)
Physical to Intangible Capital Ratio	-0.006	-0.005	-0.001	-0.002	-0.002	-0.000	0.001	-0.000	-0.001	-0.002	-0.002	0.000	0.002	-0.002
	(0.006)	(0.006)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Physical Capital to Employment Ratio	-0.005	-0.005	-0.005^{**}	0.006^{**}	0.014^{***}	-0.000	-0.005	0.006^{*}	-0.005^{**}	0.005^{*}	0.016^{***}	-0.001	-0.004	0.007^{**}
	(0.009)	(0.010)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)
Log Physical Capital	0.009	0.009	0.004^{*}	-0.005	-0.016^{***}	0.001	0.004	-0.010^{***}	0.004^{*}	-0.001	-0.019^{***}	0.001	0.005	-0.011^{***}
	(0.010)	(0.010)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)
Multi Plant	-0.002	-0.001	-0.003^{**}	-0.003	-0.001	-0.001	0.003	0.010^{**}	-0.004^{**}	-0.003	-0.001	-0.001	0.003	0.012^{***}
	(0.011)	(0.011)	(0.002)	(0.002)	(0.004)	(0.001)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)
Exporter	-0.001	0.004	0.000	0.008^{**}	0.008^{**}	-0.000	-0.006^{*}	-0.003	0.001	0.011^{***}	0.009^{**}	-0.000	-0.003	-0.008^{*}
	(0.012)	(0.012)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)
Observations	7,379	7,378	7,378	7,378	7,378	7,378	7,378	7,378	7,379	7,379	7,379	7,379	7,379	7,379
Adj. R^2	0.00919	0.000906												
Industry FE (2 digit)	Yes													
Industry FE (Aggregate)		Yes												
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald test	436.5	357.8	357.8	357.8	357.8	357.8	357.8	357.8	436.5	436.5	436.5	436.5	436.5	436.5
Kleibergen-Paap test	46.31	34.99	34.99	34.99	34.99	34.99	34.99	34.99	46.31	46.31	46.31	46.31	46.31	46.31
Underidentification test	110.4	94.16	94.16	94.16	94.16	94.16	94.16	94.16	110.4	110.4	110.4	110.4	110.4	110.4
P-value Underid. test	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A.2: Estimated results of the TSLS model using 2011 shares as instrumental variables for 2018 shares. Model 1 uses 2-digits industry fixed effects, and model 2 the same fixed effects of model 2 above.

	2nd Stage		First Stage											
			Model 1						c Model 2					
	Model 1	Model 2	ICT Eng.	Non-ICT Eng.	Non-tech. Hig. Int.	ICT Tech.	Non-ICT Tech.	Non-Tech. Int.	ICT Eng.	Non-ICT Eng.	Non-tech. Hig. Int.	ICT Tech.	Non-ICT Tech.	Non-Tech. Int.
ICT Engineers (2018)	0.249**	0.271**												
	(0.107)	(0.125)												
Non-ICT Engineers (2018)	0.006	0.095												
	(0.088)	(0.107)												
Non-technical Higher Intellectual (2018)	-0.069	-0.078												
	(0.066)	(0.070)												
ICT Technicians (2018)	-0.217*	-0.197												
	(0.119)	(0.127)												
Non-ICT Technicians (2018)	-0.092	-0.035												
	(0.067)	(0.077)												
Non-technical Intermediate (2018)	-0.020	-0.047												
	(0.047)	(0.053)												
R&D ICT Engineers (2011)			0.818***	0.027	-0.090***	-0.005	-0.003	-0.042***	0.777***	-0.002	-0.075**	-0.016	-0.024	-0.007
			(0.044)	(0.021)	(0.029)	(0.015)	(0.014)	(0.016)	(0.050)	(0.029)	(0.033)	(0.017)	(0.018)	(0.018)
Admin. & Support ICT Engineers (2011)			0.553***	0.128*	-0.034	0.138***	0.092	-0.072*	0.566***	0.092	-0.029	0.131***	0.067	-0.034
			(0.084)	(0.074)	(0.061)	(0.044)	(0.063)	(0.040)	(0.071)	(0.071)	(0.067)	(0.048)	(0.060)	(0.035)
ICT Managers (2011)			0.797***	0.147***	0.000	-0.103***	0.003	-0.069	0.743***	0.131**	0.004	-0.118***	-0.007	-0.037
			(0.083)	(0.056)	(0.063)	(0.039)	(0.018)	(0.044)	(0.086)	(0.057)	(0.061)	(0.043)	(0.018)	(0.044)
Sales ICT Engineers (2011)			0.444**	0.018	-0.001	0.076*	0.024	0.008	0.394*	0.040	-0.042	0.053	0.053*	0.041
			(0.221)	(0.068)	(0.081)	(0.041)	(0.028)	(0.040)	(0.224)	(0.066)	(0.090)	(0.043)	(0.028)	(0.040)
Telecomm. ICT Engineers (2011)			0.883***	0.061	0.101	0.092	-0.025	-0.117**	0.851***	0.003	0.253**	0.084	-0.040	-0.100
			(0.242)	(0.076)	(0.142)	(0.057)	(0.078)	(0.058)	(0.238)	(0.091)	(0.128)	(0.061)	(0.088)	(0.064)
Non-ICT Engineers (2011)			-0.008	0.697***	0.021	-0.007	0.107***	0.005	-0.001	0.596***	0.091***	0.000	0.021	0.046*
			(0.008)	(0.040)	(0.033)	(0.006)	(0.028)	(0.024)	(0.009)	(0.041)	(0.035)	(0.007)	(0.028)	(0.025)
Non-technical Higher Intellectual (2011)			0.026**	0.026*	0.599***	-0.002	0.001	0.057***	0.015	0.038***	0.570***	-0.007	0.012	0.060***
			(0.012)	(0.014)	(0.027)	(0.005)	(0.013)	(0.020)	(0.011)	(0.013)	(0.027)	(0.006)	(0.012)	(0.022)
ICT Technicians (2011)			0.023	0.042**	-0.033	0.640***	0.026	0.006	0.001	0.012	-0.012	0.634***	-0.010	0.035
			(0.034)	(0.020)	(0.023)	(0.059)	(0.018)	(0.025)	(0.036)	(0.020)	(0.026)	(0.059)	(0.019)	(0.024)
Non-ICT Technicians (2011)			-0.005	0.110***	-0.073***	0.025***	0.693***	-0.019	-0.004	0.032*	-0.020	0.033***	0.611***	0.021
			(0.004)	(0.019)	(0.013)	(0.010)	(0.038)	(0.014)	(0.005)	(0.019)	(0.013)	(0.012)	(0.039)	(0.015)
Non-technical Intermediate (2011)			-0.001	-0.004	0.069***	0.000	0.010	0.664***	0.002	0.007	0.059***	0.001	0.019***	0.635***
			(0.003)	(0.007)	(0.012)	(0.003)	(0.006)	(0.022)	(0.003)	(0.006)	(0.013)	(0.003)	(0.006)	(0.022)
Log Sales	-0.003	-0.004	-0.000	0.004*	0.016***	-0.002***	-0.003	0.009***	-0.000	0.007**	0.014***	-0.002**	-0.003	0.009***
	(0.008)	(0.009)	(0.002)	(0.003)	(0.004)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Log Age	-0.003	-0.005	-0.006***	-0.004	0.008**	-0.001	0.002	0.001	-0.005***	-0.001	0.005	-0.001	0.004	0.001
	(0.010)	(0.010)	(0.001)	(0.003)	(0.004)	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)
Fast Broadband	0.039**	0.036**	0.004	0.003	0.015**	0.002	0.003	-0.005	0.005	0.005	0.013**	0.003	0.004	-0.008
	(0.016)	(0.016)	(0.003)	(0.005)	(0.006)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)
CRM	0.039***	0.039***	-0.000	0.001	0.008**	0.002	-0.002	0.010**	-0.001	0.003	0.006	0.002	-0.001	0.011**
	(0.012)	(0.012)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)
ERP	0.021*	0.022*	0.001	0.001	0.008**	0.003**	0.003	0.000	0.001	0.003	0.005	0.002*	0.004	0.003
	(0.011)	(0.011)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)
E-commerce	0.011	0.010	-0.002	-0.007***	-0.002	-0.002	-0.004*	0.005	-0.003**	-0.008***	-0.002	-0.002	-0.004*	0.001
	(0.015)	(0.016)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.006)
Physical to Intangible Capital Ratio	-0.006	-0.005	-0.000	-0.002	-0.002	0.000	0.002	-0.002	-0.000	-0.002	-0.002	-0.000	0.001	-0.000
	(0.006)	(0.006)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Physical Capital to Employment Ratio	-0.005	-0.005	-0.004*	0.004	0.016***	-0.001	-0.004	0.007**	-0.004**	0.006**	0.014***	-0.001	-0.005	0.006*
	(0.009)	(0.010)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)
Log Physical Capital	0.009	0.009	0.003	-0.001	-0.019***	0.001	0.005	-0.011***	0.004*	-0.004	-0.016***	0.001	0.004	-0.010***
	(0.010)	(0.010)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)	(0.004)
Multi Plant	-0.002	-0.001	-0.003**	-0.004	-0.001	-0.001	0.003	0.012***	-0.003*	-0.003	-0.001	-0.001	0.003	0.010**
	(0.011)	(0.011)	(0.002)	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.001)	(0.003)	(0.004)
Exporter	-0.001	0.004	0.001	0.012***	0.009**	0.000	-0.003	-0.008*	0.000	0.008**	0.009**	-0.000	-0.006*	-0.003
	(0.012)	(0.012)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)
Observations	7,379	7,378	7,379	7,379	7,379	7,379	7,379	7,379	7,378	7,378	7,378	7,378	7,378	7,378
Adj. R^2	0.00907	0.000590												
Industry FE (2 digit)	Yes													
Industry FE (Aggregate)		Yes												
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald test	262.5	216.1	262.5	262.5	262.5	262.5	262.5	262.5	216.1	216.1	216.1	216.1	216.1	216.1
Kleibergen-Paap test	29.16	22.03	29.16	29.16	29.16	29.16	29.16	29.16	22.03	22.03	22.03	22.03	22.03	22.03
Underidentification test	119.6	101	119.6	119.6	119.6	119.6	119.6	119.6	101	101	101	101	101	101
P-value Underid. test	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hansen test	5.101	5.688	5.101	5.101	5.101	5.101	5.101	5.101	5.688	5.688	5.688	5.688	5.688	5.688
P-value Hansen test	0.277	0.224	0.277	0.277	0.277	0.277	0.277	0.277	0.224	0.224	0.224	0.224	0.224	0.224

Table A.3: Estimated results of the TSLS model using 2011 shares as instrumental variables for 2018 shares for all occupational classes, but ICT engineers, which are instrumented by specialised ICT engineering classes. Model 1 uses 2-digits industry fixed effects, and model 2 the same fixed effects of model 2 above.

B 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 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.

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