The determinants of AI innovation across European firms

Ioana Igna[♦] and Francesco Venturini[♢*]

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Abstract

Using patent data for a panel sample of European companies between 1995 and 2016 we explore whether the innovative success in Artificial Intelligence (AI) is related to earlier firms' research in the area of Information and Communication Technology (ICT), and identify which company characteristics and external factors shape this performance. We show that AI innovation has been developed by the most prolific firms in the field of ICT, presents strong dynamic returns (learning effects), and benefits from complementaries with knowledge developed in the area of network and communication technologies, high-speed computing and data analysis, and more recently in cognition and imaging. AI patent productivity increases with the scale of research, but is lower in presence of narrow and mature technological competencies of the firm. AI innovating companies are found to benefit from spillovers associated with innovations developed in the field of ICT by the business sector; this effect, however, is confined to frontier firms. Our findings suggest that, with the take-off of the new technology, the technological lead of top AI innovators has increased mainly due to the accumulation of internal competencies and the expanding knowledge base. These trends help explain the concentration process of the world's data market.

Keywords: AI; ICT; patenting; European firms

JEL Classification: O31; O32; O34

[*]**Ioana Igna**: Department of Business Administration & CIRCLE, Lund University (SE). **Francesco Venturini**: Department of Economics, University of Perugia, Via Pascoli 20, 06123 Perugia (IT) & NIESR (London, UK). Corresponding author: Francesco Venturini (francesco.venturini@unipg.it)

1 Introduction

A new wave of breakthrough technologies has been transforming how firms operate and workers are employed (Brynjolfsson and Mitchell, 2014). Artificial intelligence (AI) is argued to be the most revolutionary technology of this new generation of innovations as it enables computers to self-program and perform tasks by training from experience through Machine Learning (ML) methods (Brynjolfsson et al., 2018). AI-related (or ML-based) technologies broaden the set of tasks implementable by machines, which now can perform activities requiring cognitive abilities and execute a larger amount of manual and routinesed tasks. The number of cognitive tasks implementable by machines is expected to increase in the incoming years due to the upswing in the research on deep and convolutional neural networks (Cockburn et al., 2018).

AI is a pervasive technology, has continuously expanding applications and is capable to fuel innovations in users, behaving thus as a typical General Purpose Technology, GPT (Trajtenberg, 2018). This would reflect the highly differentiated nature of underlying knowledge which covers numerous technological fields, from Computer science to Engineering and Mathematics, including Material Science, Medicine and Chemistry (Baruffaldi et al., 2020). Early industrial applications of AI included, for instance, compound identification and genomic data management in pharmaceuticals, machine-vision defects identification in aerospace and semiconductors, image inspection elaboration in the oil industry and mining (OECD, 2018, ch. 2).

The economic impact of AI is still unknown due to the difficulties of measuring advances in this technological field and the long time required by these innovations to yield positive returns. As for any GPT, AI forces business reorganization, work reconfiguration and investment in complementary investments, yielding delayed productivity effects (Brynjolfsson et al., 2020, Venturini, 2019).[1] The economic literature has primarily focused on the labor market effects of such breakthrough technologies showing that middle-skilled employees performing manual and highly routinised tasks are exposed to a higher risk of being replaced by industrial robots (Autor et al., 2003, Acemoglu and Restrepo, 2019, Graetz and Michaels, 2018, Arntz et al., 2017). However, AI-intensive jobs are mostly classified as professionals (and associated technicians) and concentrate in knowledge-intensive sectors such as information and communication, financial and insurance activities, professional services, suggesting that AI may be replacing high-skilled workers (Squicciarini and Nachtigall, 2021, Webb, 2020).

Conceptualisation and early implementation of AI dates back to the 1950s. However, as technology producing sector, AI has developed only more recently. Gofman and Jin (2019) document that, in the US, the uptake of the AI industry was enabled by the hiring of computer science academics by large corporations, that could offer highly rewarded job positions. Beraja et al. (2020) study the role of China's government as data provider, emphasizing its effect on the development of AI (facial recognition)

[1] Goldfarb et al. (2020) propose a method to identify whether ML is a GPT using data on online job postings. They find that ML labor demand is largely diffused across industries, most ML jobs involve research tasks and are created in places where co-invention costs are lower, i.e. among large firms and in cities. This would indicate that ML has pervasive use, is capable of incremental improvement and is exploited in application sectors for research scopes.

innovation by the business sector. In Europe, the share of AI innovations on the group of technologies driving the Fourth Industrial Revolution (4IR), such as analytics, user interfaces, 3D, position determination, power supply, security, has been thus far modest, but is rapidly increasing (EPO, 2017, Benassi et al., 2019). In the last decade, AI patenting has exploded world-widely as a result of the advances in deep learning and ML-based neural network methods, combined with the massive processing power and data storage (WIPO, 2019, UK-IPO, 2019). One key aspect arising from the early literature is that AI patenting is highly concentrated in few large firms, earlier active in the sector of Information and Communication Technology (ICT), localised in narrow tech hubs. Dernis et al. (2019) illustrate that around 75% of total AI patents world-wide are applied for by top R&D performers and a primary role in AI innovation is played by software houses and IT service companies. This trend significantly contrasts with the one observed in earlier technological waves, when the bulk of innovations was developed within the manufacturing sector and the driving innovation was tangible in nature. Klinger et al. (2020) map AI innovations through scientific papers finding, consistently with the patent-based evidence, that the surge in this technlogical area is due to few prolific and narrowly-focused technology firms.[2]

Thus far, only a few works have investigated the characteristics of the firms active in AI. Alderucci et al. (2020) look at productivity differentials between AI and non-AI innovating firms in the US, documenting that the former have a considerably better performance. AI-investing firms are found to grow faster in terms of sales and employment than non-AI investing firms (Babina et al., 2020). Bessen et al. (2021) study the activity of AI startups finding that the usage of proprietary data in the development of algorithms and AI systems is crucial for their business and also for collecting venture capital funds.

Although the literature on AI is expanding, little is still known about the nature of the firms innovating in this field, to what extent their patenting performance is related to earlier research in technologically advanced areas such as ICT, and which factors explain their inventive success. This paper aims at answering these questions by investigating the determinants of AI innovation across European firms through a regression analysis that first estimates the firm probability to innovate in AI and then identifies the main drivers of AI patenting. To this aim, we build a large dataset containing information on 20,192 companies (625 AI patent holders) that applied for 219,835 patents in digital technological fields (1,977 AI patents) at the European Patent Office (EPO) between 1995 and 2016. For a sample of 409 AI innovating firms, we also merge patent information with balance sheets' data extracted from the Bureau van Dijk (BvD) Orbis dataset, and estimate a knowledge production function to identify the drivers of their patenting productivity (dynamic returns, technological capabilities, structural characteristics, knowledge spillovers, etc.).

We provide two novel pieces of evidence. First, we show that the probability to invent in AI is systematically higher for the most prolific innovators active in antecedent technology fields such as ICT. Second, in terms of patent productivity, AI innovators take advantage of strong learning effects associated with

[2] Webb et al. (2018) document the sharp increase in high-tech patenting in the US, contrasting the rise of innovations in cloud-computing, software and AI to that in other technology fields. By text mining trademarks' documents, Nakazato and Squicciarini (2021) provide evidence of the increasingly wide diffusion of AI-based products in most OECD countries.

the past development of AI innovations (dynamic returns) and of important technological complementarities with own knowledge related to ICT. Companies specialised in digital technologies such as network & communication, high-speed computing and data analysis, and more recently in cognition and imaging, are more productive in AI. On average, the development of AI makes earlier competences more obsolete, crowding out mature innovators in the technology race against relatively younger innovators. Similarly, patent productivity is lower for those companies with highly specialised technological competences. This would confirm that even for an emerging technology such as AI, diversification of competences is a requisite to achieve better innovation outcomes, as companies can exploit knowledge complementarities, common heuristics and scientific principles between contiguous technological sub-classes. Interestingly, AI inventing companies are also found to benefit from inter-firm ICT knowledge spillovers; however, this effect is not generalized, but confined to a smaller group of innovators, prevalently frontier firms. Overall, our findings suggest that, with the take-off of the new technology, the inventive success of AI companies has become more dependent on internal competencies and knowledge.

Our results are shown to be robust to several issues, namely to controlling for the structural characteristics of the firms (age, financial capacity, asset intangibility, group affiliation, etc.), the nature of patent indicators (raw counts vs quality adjusted applications), different sources of knowledge spillovers (business companies vs public research institutions), sample composition issues (ICT vs. non-ICT companies; R&D vs. non-R&D sector firms; top vs. non-top applicants, etc.), and alternative estimation methods (negative binomial vs zero-inflated regression, pre-sample fixed effects vs pseudo fixed effect data regression) and specification (static vs dynamic regression).

Our work makes an important contribution to several influential streams of the literature. First, we contribute to the line of studies searching for which factors are behind the development of AI, whether these innovations are an evolution of earlier digital technologies or they do represent a truly new technology (Lee and Lee, 2021).[3] Our evidence would suggest that, albeit technologically contiguous and complementary, there might be discontinuity between AI and ICT technologies. This result may reflect recombination of knowledge (Hoisl et al., 2015) or the selection of high-opportunity technologies (Corrocher et al., 2007); the latter require highly diversified knowledge base, have high rates of innovation but their development is increasingly concentrated in few giant firms.

Also, our work offers some useful insights for the literature on big-tech companies active in the digital markets such as internet search and software operating systems (Google, Apple, Android, etc.), social network (Facebook, Twitter, Instagram, etc.), content platform, e-commerce and product delivery (Netflix, Amazon, Alibaba, etc.), and service sharing (AirBnB, Uber, etc.). Such firms have an extraordinarily huge market power and hence their performance have important consequences world-widely on price dynamics and business dynamism (Diez et al., 2018), profitability and income distribution (Gutierrez and Philippon, 2019, Autor et al., 2020), profit shifting and tax revenue collection (World Development, 2019). These firms are at the frontier of AI technology and, based on our results, future advances

[3]An influential stream of studies uses patent data to infer the nature of General Purpose Technologies of digital technologies (Hall and Trajtenberg, 2004, Petralia, 2020).

in the field would reinforce their competitive advantage. In essence, such companies could grow even larger, endogenously determining the structure of the market in which they operate ('competition for the market').

Relatedly, our work contributes to understanding which characteristics lead big-tech firms to dominate the data market and how the relationship between industry, academia and government may change in relation to the increasing importance of data-intensive AI systems (Yu et al., 2021). An increasing deal of attention is paid to which policies may mitigate the concentration process: the acknowledgement of individual data authorship, as well as the enforcement of the protection of such rights, are argued to be effective measures to this aim (Savona, 2019).

Finally, our work sheds light on the nature of spillovers affecting knowledge generation in the current technological area, and to what extent these externalities are related to the technological or the geographical distance among innovators (Bloom et al., 2013, Lychagin et al., 2016). We show that AI innovating firms benefited from some inter-firm spillovers. However, in the latest years, the advent of big innovators with a strongly cumulative technological lead has made knowledge spillovers more uneven and confined to top innovators.

The structure of the paper is the following one. Section 2 motivates the paper and illustrates the empirical strategy. Section 3 describes the data sources and the methodology adopted for constructing the variables used in the regression analysis. Section 4 shows the rich set of econometric results and, finally, Section 5 concludes.

2 Empirical model

The purpose of this paper is to understand which European companies develop AI technologies, whether this depends on their earlier innovation in related technological fields such as ICT, and which other company characteristics or external factors help explain differentials in their patent productivity. To accomplish this task, we develop a two-fold empirical analysis: (1) a probit regression on a large sample of companies innovating in the broad field of digital technologies; and (2) a count data regression of a knowledge production function focussed on AI innovating companies.

Propensity to patent in AI

As a first approach, we implement a pooled probit regression to identify which firms have a greater probability to engage in AI innovation. We ask whether the probability to innovate (patent) in AI-related fields primarily depends on the earlier engagement in ICT and on other technological characteristics of the firm. Our regression model is specified as follows:

$$\begin{aligned} Pr(AI_{it} = 1|X_{it-1}) &= \gamma_1 ICT_{it-1} + \gamma_2 \ln Age_{it-1} \\ &+ \gamma_3 \ln TechSpec_{it-1} + \gamma_4 \ln TechBreadth_{it-1} + \eta_i + \mu_j + \tau_t + \upsilon_{it} \end{aligned} \quad (1)$$

where the dependent variable, AI, is a dummy indicating whether the company i in the industry j has filed (at least) one AI patent application at time t ($t = 1995, ..., 2016$). The set of conditioning factors, X, assumed to affect the probability to patent in AI includes proxies for the firm engament in ICT innovation, ICT, and other company characteristics, such as the inventive age, Age, the degree of technological specialisation, $TechSpec$, and the breadth of its innovation activities, $TechBreadth$.

In eq. (1), all explanatory variables are taken with a one-year lag with respect to the dependent variable to mitigate reverse causality problems; regressors which are continuous variables are expressed in logs. Firm fixed-effects are included as pre-sample means of all company's patents and are used to collect the impact of time-invariant un-observable technological capabilities. Time dummies are used to capture the effect of common technological shocks, etc. υ_{it} are stochastic error terms.

AI knowledge production function

As a second approach, we estimate a knowledge production function and identify which factors drive the patenting productivity of AI innovating companies. We consider a R&D technology consistent with the latest Schumpeterian growth studies that investigate the linkage between research effort and innovation outcomes from a dynamic perspective. This modeling framework has been used at firm level by Madsen et al. (2010), at industry level by Venturini (2012) and at country level by Ha and Howitt (2007) and Ang and Madsen (2011):[4]

$$\Delta A_{AI} = \frac{H_{AI}^{\sigma}}{L^{\varrho}} \cdot \bar{A}^{\phi} \cdot \bar{S}^{\zeta} \tag{2}$$

The creation of new (patented) knowledge, ΔA_{AI}, depends positively on human capital engaged in AI-related R&D, H_{AI}, the stock of relevant (patented) knowledge internal to the firm $\bar{A}$, and the knowledge pool (stock) external to the firm $\bar{S}$. As described below, $\bar{S}$ captures the portion of technological knowledge, geographically concentrated, which is relevant for the firm to innovate in AI. The magnitude of these spillovers is assumed to decrease with the distance between the recipient and the unit sourcing technological knowledge. L_t approximates the firm degree of product differentiation. This variable captures the dilution of research expenses across the new product projects in which the company is engaged: the larger the number of product varieties supplied by the company, the lower returns to total R&D investment. Since product varieties grow with company size, L is usually approximated by employment (or sales).

The available pool of internal knowledge, $\bar{A}$, comprises the stock of innovations patented in the key technology area where the firm operates (AI) and the stock of innovations patented in contiguous technological fields (ICT):

$$\bar{A} = A_{AI}^{\theta} \cdot A_{ICT}^{1-\theta} \qquad \theta \in [0, 1] \tag{3}$$

where θ identifies the weight of the two patent stocks on the internal knowledge pool. $\bar{S}$ approximates the pool of external knowledge and depends itself on the stock of AI and ICT knowledge patented by

[4]Following the Schumpeterian literature on innovation and economic growth, the stock of existing knowledge is denoted by A, and the flow of new knowledge by ΔA.

inventing units geographically close to the firm i (Section 3 provides details on the construction of spillover variables):

$$\bar{S} = S_{AI}^{\vartheta} \cdot S_{ICT}^{1-\vartheta} \qquad \vartheta \in [0,1] \tag{4}$$

where ϑ reflects the relative importance of the two patent stocks on the external knowledge which is relevant to the AI innovating firm.

In eq. (2), the parameter σ (> 0) quantifies returns to research investment. ϕ identifies the inter-temporal (within-firm) knowledge spillovers and hence measures dynamic returns in AI innovation. ζ captures cross-sectional (across firms) knowledge spillovers and hence measures geographical externalities. $\phi > 0$ signifies that AI firms learn about the development and the implementation of the new technology from their past innovations, resulting more productive than companies with fewer innovations in the field. Conversely, $\phi < 0$ would imply that companies more experienced in AI are less productive as technological opportunities are exhausting.[5] $\varrho(> 0)$ is the parameter of product proliferation at the level of individual firm.

Based on eqs. (2)-(4), we estimate the following empirical specification using count data regression methods:

$$\begin{aligned}\Delta A_{AI,it} = exp(\gamma_1 \ln A_{AI,it-1} \quad + \quad & \gamma_2 \ln A_{ICT,it-1} + \gamma_3 \ln S_{AI,it-1} + \gamma_4 \ln S_{ICT,it-1} + \\ & \gamma_5 \ln H_{AI,it-1} + \gamma_6 \ln L_{it-1} + \gamma_7 \ln X_{it-1} + \eta_i + \mu_j + \tau_t + \upsilon_{it})\end{aligned} \tag{5}$$

where i identifies firms, j production sectors, and t time. The dependent variable is the annual number of AI patent (count) applications, ΔA_{AI}. Patent productivity is assumed to depend on firm (patented) knowledge stock, earlier developed in the technological fields of AI and ICT (A_τ with $\tau = AI$ or ICT), the pool of knowledge in the reference technological fields developed by neighbouring inventive units (S_τ with $\tau = AI$ or ICT), human resources allocated by the firm to AI innovation (H_{AI}), a measure of product proliferation (L), and a set of company characteristics (technological competences, etc.), which are included in the vector X. η are firm-specific fixed effects, μ industry-specific fixed effects (2-digit NACE Rev. 2 classification) and τ's are common time dummies. υ_{it} are the error terms.[6]

As discussed above, the coefficient of A_{AI} (or A_{ICT}) should capture the persistency of innovative processes, with a positive value of γ_1 (or γ_2) indicating that the most prolific patenting firms have a competitive lead over less innovative companies (and new entrants) in creating new (patentable) knowledge in the area of Artificial Intelligence. In this context, we also investigate whether AI patent productivity is

[5] Clancy, 2018 develops a combinatorial model of innovation, which is tested on US patent data, driven by the two opposing forces of learning ($\phi > 0$) and fishing-out ($\phi < 0$).

[6] In our regression framework, the coefficients of the logged explanatory variables represent elasticities. This allows to map the empirical coefficients to the theoretical parameters as follows: $\gamma_1 = \phi \cdot \theta$, $\gamma_2 = \phi \cdot (1-\theta)$, $\gamma_3 = \phi \cdot \vartheta$, $\gamma_4 = \phi \cdot (1-\vartheta)$, $\gamma_5 = \sigma$, and $\gamma_6 = \varrho$. Note that the full set of theoretical parameters can be identified only in estimates using data matching patent information and company balance sheets, from which we extract a measure of firm employment, useful to estimate γ_6 (Section 4.2.2). In the remaining of the paper, we estimate γ_1 - γ_5. In all regression tables, standard errors are clustered at firm level and over time.

related to some specific areas of ICT, inspecting which of the latter technologies generate steeper dynamic returns (if any). These sub-fields would therefore represent the technological antecedents of AI. Not less relevantly, this exercise will help identify which companies are more likely to succeed in AI innovation and lead the market.

One caveat of the analysis is that we are unable to account for the firm usage of data, which is found to be a crucial input to train algorithms and develop AI innovations (Bessen et al., 2021). In essence, here we assume that training data are complementary to other innovation inputs such as human capital and, as long as its usage is persistent over time, the effect of the unmeasured factor is captured by the lagged stock of AI patents.

Our regression analysis builds upon Bloom et al. (2013) and estimates eq. (5) using a panel count data model with the pre-sample mean scaling method to account for firm heterogeneity. In essence, we control for company time-invariant characteristics (propensity to patent) by including into the specification the average value of the dependent variable observed in the pre-estimation period (see also Blundell et al., 1999). Computing the pre-sample mean back in time with respect to the interval of the regression has the advantage of reducing endogeneity bias; however, it increases measurement errors if companies have changed the technological areas of their inventing activity over time. We primarily calculate the pre-sample patent propensity of each company as mean value of AI patent applications from 1978 to 1995, but then perform some robustness checks using different time windows.

Our main estimation is based on the negative binomial regression. However, the robustness of the results is assessed using alternative estimators, such as the zero-inflated regression model to assess the excessive incidence of zeros in the dependent variable; and the panel (within-transformation) negative binomial regression in order to model company fixed effects differently. We assess the stability of results along different dimensions. First, we estimate our regression model over different time horizons, the overall period 1995-2016 and the sub-period 2009-2016. Restricting the analysis to the latter time interval allows to neutralize the break effects associated with the global crisis of 2008-09 and, above all, to focus on the take-off period of the AI economy. Second, we conduct a careful investigation on sample composition issues and re-estimate the model excluding companies from the European technologically leading country (Germany), companies active in ICT production or in the R&D sector and, finally, companies that are at the frontier of AI technology. This assessment will allow us to establish whether there are differentiated effects of the explanatory variables between areas, sectors and type of companies. In additional robustness checks, we explore the nature of knowledge spillovers by distinguishing patent activities by private businesses, public research bodies and, residually, individual inventors.

As in Bloom et al. (2013), in our regression model, dynamics of the innovation process is accounted for by taking regressors one-year lagged with respect to the dependent variable that, as discussed above, also helps mitigate reverse causality problems. From an econometric point of view, our regression model is *implicitly* dynamic as the lagged value of the dependent variable is incorporated into the lagged value of the AI patent stock. Though, in robustness checks, we formulate our specification as *explicitly* dynamic by including the lagged dependent variable on the right-hand side so to better study the degree of persistency

in AI innovation processes.

3 Data description

3.1 Data source and methods

The empirical analysis is performed on two panel samples of firms from 28 European countries plus Turkey that demanded for patent protection at the European Patent Office between 1978 and 2016.[7] Our data are extracted from the OECD, EPO PATREG database, release July 2019 (see Maraut et al., 2008).[8]

For the probit regression, we consider all firms that applied for patents in the technological fields of Artificial Intelligence and Information and Communication Technology. To identify patent applications in the area of ICT we adopt the IPC-based taxonomy (J-tag) recently developed by Inaba and Squicciarini (2017). To identify patent applications in the area of AI, we adopt the classification developed by EPO (2017, Annex 1). Since the J-tag taxonomy covers some AI categories, applications under these classes are removed from the group of ICT innovations. Although patent information is available from 1978, we restrict the regression analysis to the period between 1995 and 2016, so to have a sufficient number of data points to build precise pre-sample patent means and, in the meantime, cover the upswing of both ICT and AI technologies.

Our probit regression considers a sample of 20,192 companies, of which 625 are AI companies. For each applicant, we build indicators of technological performance, exploiting information contained in the patent document as made available in the PATREG database. As key explanatory variable, we consider three alternative indicators of ICT patenting: a simple binary variable for those companies patenting at least once in ICT; a set of dummies identifying the quartiles of the distribution of the ICT patent portfolio where each company lies; or a continuous variable defined by the firm's stock of ICT patents (and its square to capture non-linearities in the impact of this explanatory variable). As controls we use the inventive age of the firm, defined as the number of years from the first application in the digital fields; the degree of specialisation of the firm technological competencies, defined as the Herfindahl-Hirschman concentration index of the technological classes covered by company patents (based on 8-digit IPC categories), which is the inverse of technology diversity index (Garcia-Vega, 2006); and the average number of patent claims, used as a proxy for the technological breadth (scope) of firm innovation (Hall et al., 2001).

To estimate our knowledge production function, we consider a sample of 409 companies that applied for AI patent applications between 1995 and 2016. These firms are identified matching patent information

[7] See Table A.1 in the Online Appendix for a breakdown of sampled companies by country.

[8] The PATREG database is used as source for patent information as OECD implements a procedure of text cleansing and geographical mapping that facilitates the matching between patent data and company balance sheets, used in the second part of the work. Additional (own-made) string cleansing and disambiguation on applicant/inventor name and address is made to increase the success rate of the matching procedure between datasets and to ensure unequivocal identification of individual applicants/inventors.

with balance sheets data extracted from Bureau van Dijk (BvD) Orbis dataset (Europe). To this aim, we first identify all (disambiguated) firms demanding for patent protection at EPO for inventions falling in the fields of AI, as of the classification developed by EPO (2017, Annex 1).[9] Then, we link the full list of AI applicants to the Orbis database (available from 2009 on) through disambiguated company's name and address. For unmatched companies, we perform an ad-hoc (manual) search to recover those applicants that have changed name or address after the application date.

For each company, we compute the annual number of raw patent counts as dependent variable ($\Delta A_{AI,it}$). The patent stock is obtained with the perpetual inventory method from the annual flows of patent applications: $A_{\tau,it} = \Delta A_{\tau,it} + (1-\delta) \times A_{\tau,it-1}$, with $\tau = AI$ or ICT. The initial stock is computed as $A_{\tau,i0} = \Delta A_{\tau,i0}/(g+\delta)$, where $t = 0$ is the year of first occurrence in the REGPAT database, g is the average annual rate of change between the first and the last occurrence over the entire time interval 1978-2016. δ is the obsolescence rate of AI/ICT related knowledge that we set to a standard rate of 15% per year. Though, we assess the sensitivity of our results to this assumption, and adopt a much faster depreciation rate (40% yearly) for such technological knowledge, based on the decay rate for R&D-based knowledge estimated by Li and Hall (2020) for the US software industry. Since our patent count indicator consists in a raw measure of innovation and does not account for heterogeneity in the patent quality (in terms of technological breadth, derivativeness, etc.), we also build alternative innovation indicators, weighting each patent application with the number of prior arts claimed (Hall et al., 2001). These data are extracted from the OECD Patent Quality Indicators database and matched with the OECD REGPAT database (see Squicciarini et al., 2013). In the Online Appendix, we assess the stability of estimates by considering a much wider array of patent quality indicators.

Our spillover variables are computed as inverse-distance weighted sums of the patent stock of neighbour inventive units. As donor units, we consider the full set of patent stocks held by businesses, universities and individual inventors. The distance between recipient and donor units, denoted by i and k respectively, are computed as Euclidean distance expressed in kilometres (d_{ik}). In our main estimates, we adopt a proximity matrix that assumes a linear decay $1/d_{ik}$:

$$S_{\tau,it} = \sum_{k=1}^{K} 1/d_{ik} \cdot A_{\tau,kt} \qquad \text{with} \;\; \tau = AI \text{ or } ICT \;\; \text{and} \;\; 1/d_{ii} = 0 \tag{6}$$

where the total number of applicants is 858 for AI and 22,124 for ICT.

In the second part of the analysis, we use two sets of control variables. The former captures the technological characteristics of the innovating company and, as above, are derived from information included

[9] Since this classification is based on the Cooperative Patent Classification (CPC) scheme (May 2017 update), AI-related CPC classes are first converted into International Patent Classification (IPC) categories —that are used in OECD EPO Patreg —using the concordance table provided by the European Patent Office. https://www.cooperativepatentclassification.org/cpcConcordances. EPO has developed a cartography to map inventions (patents) underpinning the 4IR EPO (2017, pag. 23-24), based on 320 CPC classes. These categories have been identified ex-ante by patent examiners and then have been verified by applying ad-hoc queries against the EPO's full-text patent database using text mining procedures. We identify 45 categories (sub-classes) related to AI and its applications, falling in Section A, B, F and G of the IPC classification.

in the patent document as available in the REGPAT database. Along with the measures of technological specialisation used in the probit regression (see above), we build three indicators capturing the effort made by the firm in AI innovation. First, for each AI application, we compute the size of the inventive team involved in the inventive process, looking at the number of (disambiguated) inventors reported in the patent document. This variable corresponds to the empirical counterpart of human capital allocated by the firm to AI research (H_{AI} in eq. 5). Second, we construct a measure of external collaborations, looking at the annual number of AI inventions co-patented by each firm with (disambiguated) other companies and public research institutions. Third, we build a binary indicator for the maturity of the firm in AI patenting activities; this variable takes the value of one for those companies with an inventive tenure above the median of the sample.

Our second set of control variables reflects the structural characteristics of the firm and are built exploiting information contained in companies' balance sheets: size (number of employees) which is our proxy for product proliferation, firm age (number of years from the establishment), group affiliation (categorical variable), asset intangibility (the ratio of intangibles to total fixed investments), the liquidity ratio (debts over current liabilities) and, finally, mark-up (ratio between operating profits and net sales). Table A.2 of the Online Appendix lists all variables used in our regressions analyses.

Table 1: **Summary statistics: Patent productivity in digital fields - AI vs ICT firms** (1995-2016)

	All patents	AI patents	ICT patents	
			AI & ICT patent holder	ICT patent holder
Patent counts	219,835	1,977	114,172	103,686
Number of firms	20,192	625	445	19,122
Patents per innovator	5.1	1.6	37.0	2.6
SD	36.2	2.3	130.0	8.5
Max	1,908	35	1,908	283

3.2 Summary statistics

In the first part of the analysis, our sample of firms is composed by 20,192 inventive units (Table 1): 625 companies that applied for AI patents between 1995 and 2016 (of which 445 units applied both in AI and ICT fields), and 19,122 companies that did innovate only in the ICT field. Taken together, our sample of companies applied for 219 thousand patents: 217 thousands were ICT applications and 1,977 were AI applications. The majority of ICT patent applications were filed by firms that also applied for AI patents (AI patent holders): 114 thousands against 103 thousand applications by the group of companies without AI patents (non-AI patent holders). Dividing patent applications by the number of patent holders, we observe that each AI patentee has on average 1.6 applications, and that ICT applications of the firms also innovating in AI (AI patent holders) are much more numerous than for non-AI patent holders (37 vs

2.6). These figures clearly show the skewness of ICT patent distribution and that, at the top tail, there is a group of very productive companies which is also engaged in developing AI innovations.[10]

Figure 1 maps the geographical distribution of AI and ICT patents of our firms across European regions (at NUTS2 level). There is a wide overlap in the regional specialisation in the two technological fields, with AI patenting activities still concentrated in few leading areas compared to ICT, mainly Germany and some other European Central regions.[11] Figure A.1 of the Online Appendix illustrates the total sum of AI and ICT patents by country.

We estimate the knowledge production function estimation on a sample of 409 companies (Table 2). The average number of AI patents is 0.20 per firm, with a standard deviation of 0.6. The stock of ICT patents owned by each of these firms is several times higher than the cumulative of AI patents (32 vs 0.8 per firm). On average, 3 inventors were involved in each AI innovation patented. AI innovating companies are quite mature in terms of research engagement in the field, have highly specialised technological competences and do not undertake much research collaborations for developing this type of technologies. See Table A.3 of the Online Appendix for full summary statistics on this group of companies.

Table 2: **Summary statistics, restricted sample** (409 firms)

	1995-2016		2009-2016	
	Mean	SD	Mean	SD
AI patents	0.16	0.60	0.20	0.67
AI patent stock	0.81	2.06	1.07	2.31
ICT patent stock	32.1	190.5	47.4	249.2
AI inventive team	3.21	3.14	3.49	3.60
AI collaborations	0.01	0.10	0.01	0.12
Tech specialisation	0.68	0.69	0.73	0.77
AI maturity	0.87	0.34	0.83	0.37
AI spillover (firm)	3.19	8.67	4.06	11.28
ICT spillover (firm)	255.2	1213.0	357.6	1606.7

4 Results

4.1 Propensity to patent in AI

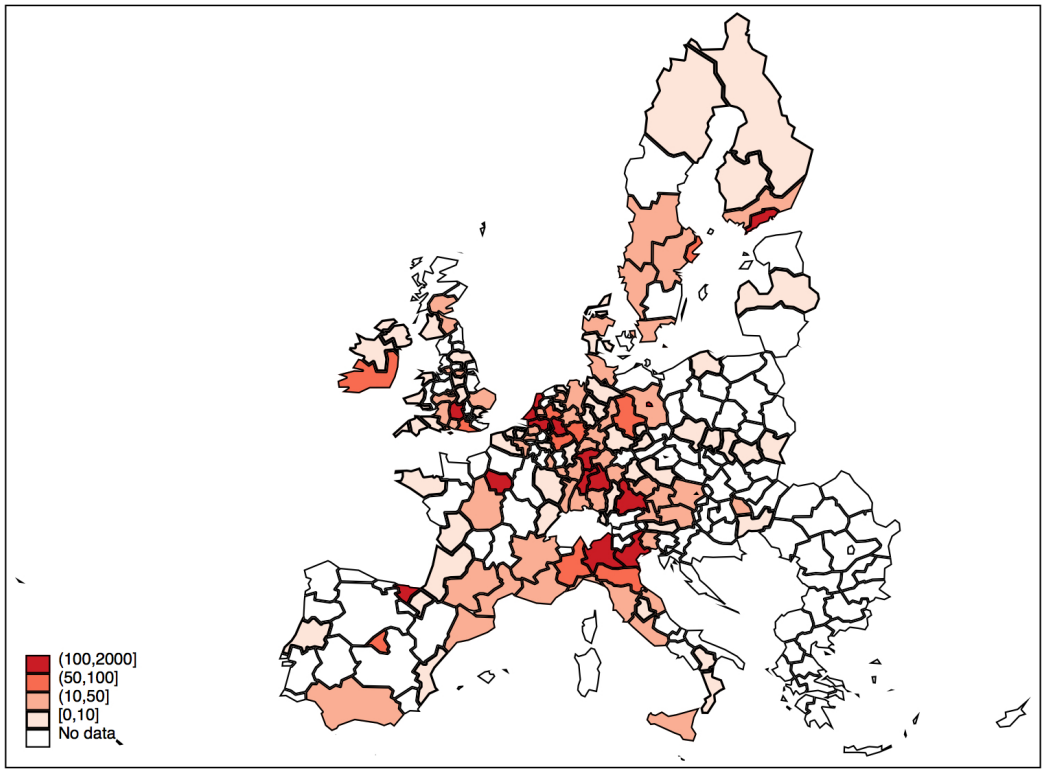
Results of our analysis on the drivers of the firm propensity to patent in AI (eq. 1) are shown in Table 3. A company patenting in ICT has a 0.4 higher probability to innovate in the new technological field (col.

[10] In the estimation of the knowledge production function, we leave out Siemens AG due to the difficulty to unambiguously match patent applications and company balance sheets between headquarter and affiliated companies. Siemens AG accounts for around one fourth of total AI patents at EPO.

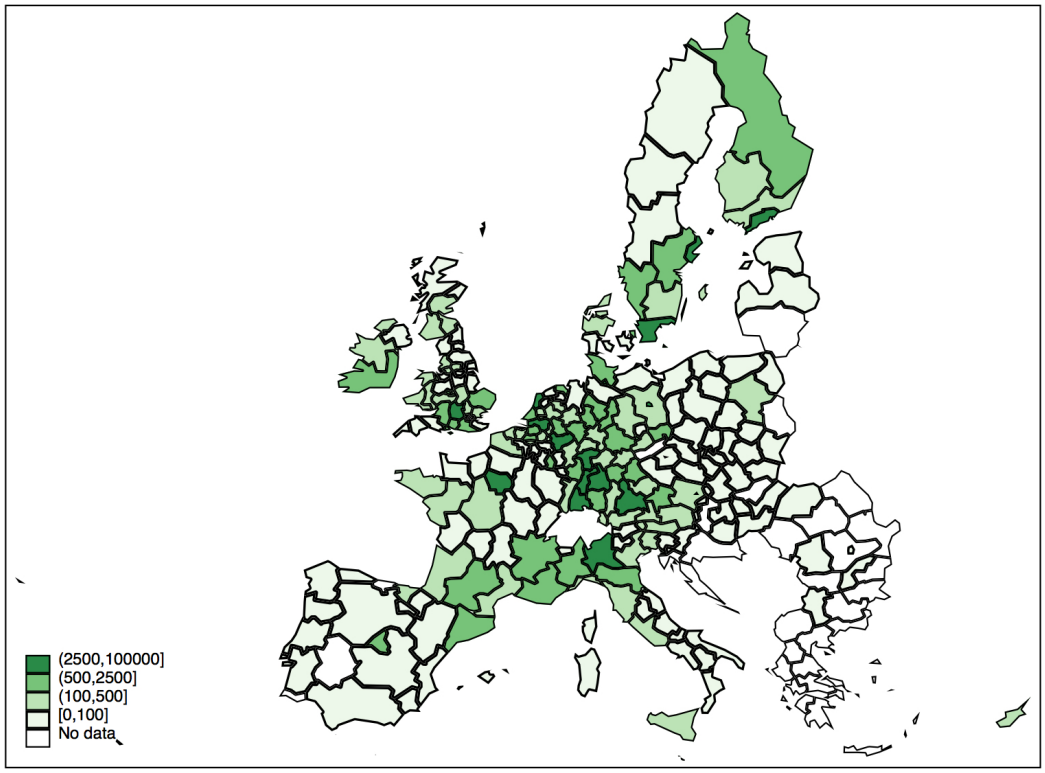
[11] See Evangelista et al. (2015) for a study on the long-run trend in European regional specialisation on key enabling and fast growing technologies.

Figure 1: **AI and ICT patenting in European regions** (1995-2016)

(a) AI patents



(b) ICT patents



1). This attitude increases with the intensity of firm engagement in ICT. Column (2) indeed shows that moving across quartiles of the distribution of the ICT patent portfolio raises the probability to patent in AI by half point. In column (3) and (4) we approximate the company engagement in ICT using the stock of ICT patents and the squared value of this variable. We find that the propensity to patent in AI increases less than proportionally with the effort in the antecedent technology. This result also holds when including our set of control variables (cols. (5)-(8)). It emerges that, other things being equal, companies having a longer inventive tenure has a higher probability to innovate in AI, whilst those with specialised technological competences or broad-scope innovations, are less likely to patent in AI. These findings suggest that experienced innovators have greater chances to move to the new technology, but their inventive success requires more diverse competences to facilitate sperimentation and combine knowledge underlying AI. Reasonably, firms owning innovations with a larger technological breadth (scope) have fewer incentives to move to the new technology.

Table 3: **Propensity to patent in AI** (20,192 firms, 1995-2016)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT patenting	binary	0.435***							
		(0.028)							
ICT portfolio (2nd quartile)	binary		0.868***						
			(0.053)						
ICT portfolio (3rd quartile)	binary		1.303***						
			(0.092)						
ICT portfolio (4th quartile)	binary		1.849***						
			(0.222)						
ICT patent stock (log)	continuous			0.183***	0.374***	0.144***	0.229***	0.387***	0.215***
				(0.015)	(0.042)	(0.043)	(0.042)	(0.041)	(0.052)
ICT patent stock^2 (log)	continuous.				-0.036***	-0.012*	-0.030***	-0.028***	-0.030***
					(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age (log)	continuous					0.198***			0.069**
						(0.028)			(0.029)
Tech specialisation (log)	continuous						-0.335***		-0.335***
							(0.019)		(0.020)
Tech breadth (log)	continuous							-0.183***	-0.231***
								(0.033)	(0.040)
Obs.		444,224	444,224	444,224	444,224	444,224	444,2246	444,224	444,224
Firms		20,192	20,192	20,192	20,192	20,192	20,192	20,192	20,192

Notes: Probit estimates. Dep. variable: AI patenting (dummy). All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. All regressors are one-year lagged w.r.t. the dependent variable. Except than for *ICT patenting* and *ICT patent portfolio* (dummy variables), all regressors are continouos variables and are expressed in logs. A *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2 Knowledge production function

In this section, we present estimates for our knowledge production function (eq. 5). We start with a set of baseline results that we then refine by identifying which area of ICT is a major technological antecedent of AI and controlling for firm structural characteristics, the effect of the sample design, the measurement of innovation quality, the nature of spillovers and the adoption of alternative econometric methods.

4.2.1 Baseline estimates

Table 4 reports estimates for the determinants of AI patent productivity. The first part of the table considers the overall time interval from 1995 to 2016. The second part restricts the focus on the post-2009 period.

Regression in column (1) includes the lagged stock of AI and ICT patents as regressors. The coefficients of these variables give insights on the cumulative advantage, or dynamic returns, in innovation processes in the emergent technological area. The patent productivity of AI companies is 0.74% higher for those with knowledge accumulated in the field, and 0.12% higher if they had previously innovated in the area of ICT. These estimates point to slightly decreasing inter-temporal (within-firm) returns in AI patenting, either when we consider individually or together the coefficients of A^{AI} and A^{ICT}.[12]

Table 4: **Baseline estimates** (409 firms, 1995-2016 and 2009-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			1995-2016					2009-2016		
AI patent stock	0.742***	0.678***	0.236***	0.155***	0.670***	0.661***	0.627***	0.613***	0.074	0.093
	(0.058)	(0.077)	(0.056)	(0.034)	(0.077)	(0.076)	(0.104)	(0.103)	(0.089)	(0.105)
ICT patent stock	0.121***	0.083**	0.193***	0.079**	0.084***	0.085***	0.189***	0.194***	0.173**	0.170**
	(0.024)	(0.032)	(0.050)	(0.031)	(0.032)	(0.032)	(0.050)	(0.050)	(0.077)	(0.077)
AI inventive team		0.251**	0.068	0.491***	0.243**	0.233**	0.276*	0.259	-0.002	-0.010
		(0.116)	(0.188)	(0.130)	(0.116)	(0.116)	(0.164)	(0.166)	(0.335)	(0.341)
AI collaborations		0.562	0.522	0.673	0.595	0.646	1.153	1.211*	2.359***	2.535***
		(0.529)	(0.939)	(0.670)	(0.534)	(0.534)	(0.710)	(0.708)	(0.752)	(0.770)
Tech specialisation		-0.223***	-0.050	-0.245***	-0.222***	-0.227***	-0.088	-0.091	-0.005	-0.034
		(0.061)	(0.088)	(0.063)	(0.061)	(0.061)	(0.106)	(0.107)	(0.194)	(0.201)
AI maturity (dummy)		-2.347***	-4.798***	-2.273***	-2.344***	-2.342***	-2.191***	-2.197***	-2.914***	-2.943***
		(0.073)	(0.114)	(0.072)	(0.072)	(0.073)	(0.112)	(0.112)	(0.216)	(0.210)
AI spillover (firm)					0.051		0.042		0.118	
					(0.033)		(0.051)		(0.076)	
ICT spillover (firm)						0.074***		0.083**		0.146**
						(0.027)		(0.041)		(0.071)
Patent indicator	Counts	Counts	Quality adjusted	Counts	Counts	Counts	Counts	Counts	Counts	Counts
Knowledge obsolescence	15%	15%	15%	40%	15%	15%	15%	15%	15%	15%
Pre-sample	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Obs.	8,998	8,998	8,998	8,998	8,998	8,998	3,272	3,272	1,024	1,024
Firms	409	409	409	409	409	409	409	409	128	128
alpha	1.650	0.944	0.103	1.252	0.933	0.921	0.669	0.662	0.173	0.168
Log-likelihood	-3479	-2923	-439.8	-2998	-2922	-2920	-1229	-1227	-446.7	-445.8
Pseudo R-squared	0.116	0.257	0.265	0.238	0.258	0.258	0.259	0.260	0.288	0.289

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects (except than in cols. (9) and (10)), 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The magnitude of these effects remain confirmed when we include into the regression our proxies for the technological characteristics of the firm (column (2)). The parameter size of AI patent stock reduces to 0.68 suggesting that, before, the coefficient of this variable was in part capturing the impact of the AI inventor team. Indeed, returns to AI research, as measured by the average number of inventors per

[12]The sum of the coefficients of AI and ICT patent stocks is equal to 0.86 and is statistically different from the unity (Wald test p-value is 0.006).

AI patent, are positive and statistically significant: firms with larger AI inventive teams have a 0.25% higher patent productivity, in line with estimates of earlier studies conducted at the firm (Kaiser et al., 2015) or inventor level (Schettino et al., 2013). There is a statistically insignificant difference in patenting performance between companies with and without technological collaborations. Conversely, firms with a greater maturity in AI patenting, i.e. those with an above-median number of years from the first AI patent filing, innovate less than firms with a younger patent track. This finding would indicate that the latest developments of AI technology have been making earlier competences more obsolete, crowding out mature innovators in the technology race against younger innovators. Similarly, patent productivity is lower for those companies with highly specialised technological competences. This would confirm that even for an emerging technology such as AI, diversification of competences is a requisite to achieve better innovation outcomes, as companies can exploit knowledge complementarities, common heuristics and scientific principles between contiguous technological sub-classes (Breschi et al., 2003).

In column (3), we run the regression model using patent variables weighted by a quality index reflecting the breadth of innovation, i.e. the number of claims. The cumulativeness of innovation processes, as captured by the coefficient of AI and ICT patent stocks, is confirmed in this regression. However, the inventive premium associated with having developed (patentable) knowledge in the AI field in the past is downsized with respect to the regression using simple patent counts (see col. (2)). By contrast, the coefficient of ICT stock is somewhat larger.

In column (4) we report estimates using raw patent indicators, but considering the value of patent stocks obtained assuming an annual rate of technological obsolescence of 40%. In this regression, the inter-temporal (within-firm) spillover is economically much smaller but continues to be statistically significant. Being still unknown the rate at which AI-related knowledge obsolesces, estimates in column (2) and (4) have to be considered as extreme (upper and lower) bound values for dynamic returns featuring AI knowledge production.

Next, we assess whether AI innovating companies have benefited from spillovers yielded by knowledge developed in the relevant technological fields. In column (5) and (6), we report results obtained using the pool of knowledge developed by private companies (see below for further results). These regressions point to a statistically significant and economically important spillover effect associated with ICT-related knowledge (0.074), but not with the pool of external AI knowledge.

On the right-hand side of Table 4, we report the results for the latter part of the sample period (2009-2016). Over this shorter interval, the size of the AI inventive team and the specialisation of technological competences do not have any effect on AI patent productivity, whilst the impact of the other covariates remains largely confirmed. The lack of significance of AI team is due to the fact that this variable, as all regressors, is taken time $t-1$ and hence its effect is partly captured by the coefficient of the AI patent stock.[13]

In columns (9) and (10), we restrict the analysis to those firms that filed AI applications only from

[13]Note that the parameter of AI inventive team turns out to be significant when this covariate is taken as contemporaneous to the dependent variable (the coefficient is 1.3), or the model is run excluding the firm stock of AI patents (the coefficient is 0.6). These estimates are not reported but are available from the authors upon request.

2009 (128 out 409 firms), in order to understand whether there are differences in AI patenting between these companies that entered the AI technology market only more recently and those with a longer innovative tenure.[14] As expected, for new entrants, there is no evidence of cumulativeness in the AI patenting process, given the relatively small knowledge acquired in the field. These firms, however, do seem capable of exploiting the competencies cumulated in ICT as well as more tenured innovators (0.17 vs 0.19 as reported in col. (8)). Among new entrants, those undertaking research collaborations are much more prolific (2.5).

4.2.2 Further analysis and Robustness checks

Searching for technological persistencies and discontinuities

As a first deepening of our analysis, we seek to identify areas of technological similarity and discontinuity between AI and ICT, investigating whether AI patent productivity relates to the specialisation in given sub-fields of the latter technologies. To this aim, we re-estimate our knowledge production function disentangling the ICT patent stock into four main components: *(i) Network & Communication*; *(ii) High-speed computing, Storage & Data analysis*; *(iii) Cognition, Imaging & Sound*; and *(iv) Measurement, Sensors & Others*.[15] In this way we can infer the ease of redirecting invention trajectories between contiguous technologies, comprehend which sub-fields can be regarded as close antecedent of the new technology and identify which companies are more likely to lead the market for AI.

Table 5 compares the baseline results obtained using the total stock of ICT patents, with estimates yielded using the cumulative value of various sub-aggregates of ICT and then including controls as in Table 4. If we consider data for the period 1995-2016, companies innovating in the field of *Network and Communication* and *High-speed computing, Storage & Data analysis* turn out to be more successful in AI, whilst those specialised on technologies for *Measurement, Sensors & Others* have a lower inventive productivity. This pattern of results slightly differs from 2009 when specialisation on *Cognition, Imaging & Sound* is found to significantly fuel AI patenting, whilst companies active in *High-speed computing, Storage & Data analysis* have a lower patent productivity. The latter finding may be explained with the fact that AI innovations are increasingly dependent on training data (and other intangibles) and hence past patents may have become an imprecise proxy for the knowledge relevant to develop the next generation of AI technologies. Another explanation is that advances in AI may have become so fast (or complex) to make innovations in *High-speed computing, Storage & Data analysis* rapidly obsolete and

[14] Regressions in columns (9) and (10) do not include pre-sample fixed effects. Following Bloom et al. (2013), in all other regressions, we use a dummy variable for those firms without AI patents before 1995, i.e. having pre-sample mean patent values equal to zero.

[15] The OECD J-tag classification includes thirteen types of ICT innovations that we group as follows (Inaba and Squicciarini, 2017): *(i) Network and Communication*: High speed network, Mobile communication, Information communication device. *(ii) High-speed computing, Storage & Data analysis*: High speed computing, Large-capacity and high speed storage, Large-capacity information analysis. *(iii) Cognition, Imaging & Sound*: Cognition and meaning understanding, Human-interface, Imaging and sound technology. *(iv) Measurement, Sensors & Others*: Security, Sensor and device network, Electronic measurement, Others.

hence un-influential for the technological developments in the field.

Our analysis integrates evidence provided by some recent works on knowledge similarity among new enabling technologies and the degree of technological originality of AI innovations with respect to digital technologies. Consistently with our results on technology antecedents, Martinelli et al. (2021) find that AI-related knowledge turns out to be very similar to knowledge developed in the fields of cloud computing and big data. Lee and Lee (2021) document that, in absolute terms, AI looks particularly original with respect to ICT and the other innovations of the Third Industrial Revolution (3IR). However, controlling for the upward trend in patent originality common to all 4IR technologies, AI is not found to behave differently from 3IR technologies. Since AI is found to affect technology development in relatively narrow fields, the new technology is also doubted to act as GPT.

Table 5: **Technological antecedents of AI** (409 firms, 1995-2016 and 2009-2016)

	(1)	(2)	(3)	(4)	(5)	(6)
		1995-2016			2009-2016	
AI patent stock	0.742***	0.767***	0.656***	0.692***	0.713***	0.649***
	(0.058)	(0.055)	(0.075)	(0.073)	(0.067)	(0.101)
ICT patent stock	0.121***			0.106***		
	(0.024)			(0.035)		
Network & Communication		0.078**	0.104**		0.086*	0.140**
		(0.035)	(0.047)		(0.049)	(0.069)
High-speed computing, Storage & Data analysis		0.203***	0.147**		0.184**	0.143
		(0.058)	(0.070)		(0.085)	(0.095)
Cognition, Imaging & Sound		-0.031	0.161**		0.147*	0.303**
		(0.064)	(0.081)		(0.089)	(0.118)
Measurement, Sensors & Others		-0.133**	-0.168***		-0.183***	-0.180**
		(0.054)	(0.062)		(0.069)	(0.075)
AI inventive team			0.228*			0.253
			(0.120)			(0.177)
AI collaborations			0.739			1.349*
			(0.527)			(0.713)
Tech specialisation			-0.174***			-0.054
			(0.059)			(0.100)
AI maturity (dummy)			-2.405***			-2.293***
			(0.073)			(0.116)
ICT spillover (firm)			0.087***			0.110**
			(0.028)			(0.044)
Obs.	8,998	8,998	8,998	3,272	3,272	3,272
alpha	1.650	1.603	0.846	1.214	1.180	0.574
Log-likelihood	-3,479	-3,462	-2,889	-1,437	-1,419	-1,194
Pseudo R-squared	0.116	0.121	0.266	0.133	0.144	0.280

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. ICT patent stock is the sum of stock of patents in *Network & Communication*, *High-speed computing, Storage & Data analysis*, *Cognition, Imaging & Sound* and *Measurement, Sensors & Others*. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Controlling for structural characteristics

Next, we ascertain whether the patent performance of AI companies is also influenced by some structural characteristics that, if not properly accounted for, could bias the effect estimated for the technological capabilities of the firm. Due to data constraints, this sensitivity analysis is confined to the period between

2009 and 2016. The number of employees and the firm age are used to understand whether companies with more formalized, or more structured, organisations are capable to undertake more complex activities, such as AI-related research, and benefit from these projects in terms of greater innovation outcomes. We also consider whether companies belonging to the same business group have a differential patenting performance compared to independent companies: within a group, the headquarter may strategically spread or concentrate research activities (or patents) across different branches (Castellani, 2017). We also control for whether firms with less stringent liquidity conditions patent significantly more than companies with less internal funds (Scellato, 2006); this condition could be structural and not be necessarily associated with the contingency of the financial crisis that followed the Great Recession of 2008-09 (Hingley and Park, 2017). Another potentially relevant factor is the degree of asset intangibility, with companies with a larger investment share of intangibles being more prone to expand the array of firm-value enhancing assets. Although the evidence on the linkage between intangible investments and patenting is still sparse (Madsen et al., 2020, Table 3), it is relatively established that investments in organisational capital, R&D and patents are all correlated and raise the market value of the firm (Rahko, 2014). Not less relevantly, we include into the regression a measure of the firm mark-up, so to identify whether companies with a greater profitability also have a better technological performance. Admittedly, all these controls are included in the regression to mitigate omitted variables problems but we do not make any assumption concerning the direction of causality between these regressors and the dependent variable.

Results in Table 6 show that firm age and (to some extent) firm size are the only variables significantly and positively associated with AI patent productivity. This can be explained with the fact that all controls identify a set of pre-conditions enabling companies to undertake research but, then, the outcome of these activities (measured in terms of patenting) does largely depend on the technological capabilities of the firm.

Sample composition issues

We now evaluate whether our estimates are affected by sample composition issues and in particular whether they are driven by some specific groups of companies (Table 7). As a first check, we remove AI firms from Germany. This country is the technological leader in Europe both for number and patent productivity of the companies active in the emerging technological area. In our sample, German companies account for one fourth of the total (112 out 409). Nonetheless, both for regression periods, the main pattern of results remains unchanged when this group of firms is omitted, excluding for instance the possibility that ICT spillovers are confined within the geographical area with the greatest concentration of innovators (cols. (2) and (8)).

Next, we exclude from the regression two distinct sectoral groups of companies.[16] The first is the

[16]The ICT sector includes the categories of Manufacture of computer, electronic and optical products (26), Telecommunications (61), Computer programming, consultancy and related activities (62), and Information service activities (63), as of the NACE rev. 2 classification. The R&D sector includes the category Scientific research and development (72).

Table 6: **Estimates with controls for structural characteristics** (409 firms, 1995-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI patent stock	0.613***	0.618***	0.610***	0.608***	0.616***	0.610***	0.615***	0.608***
	(0.103)	(0.103)	(0.104)	(0.104)	(0.102)	(0.102)	(0.103)	(0.102)
ICT patent stock	0.194***	0.172***	0.188***	0.200***	0.193***	0.193***	0.194***	0.176***
	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)	(0.050)	(0.050)	(0.048)
AI inventive team	0.259	0.272	0.266	0.252	0.253	0.255	0.260	0.261
	(0.166)	(0.170)	(0.164)	(0.164)	(0.168)	(0.164)	(0.166)	(0.163)
AI collaborations	1.211*	1.198*	1.204*	1.270*	1.157*	1.301*	1.169*	1.272*
	(0.708)	(0.686)	(0.710)	(0.721)	(0.703)	(0.708)	(0.695)	(0.688)
Tech specialisation	-0.091	-0.093	-0.102	-0.089	-0.087	-0.088	-0.090	-0.099
	(0.107)	(0.105)	(0.104)	(0.107)	(0.106)	(0.106)	(0.107)	(0.104)
AI maturity (dummy)	-2.197***	-2.203***	-2.233***	-2.191***	-2.193***	-2.209***	-2.202***	-2.256***
	(0.112)	(0.111)	(0.111)	(0.111)	(0.111)	(0.110)	(0.113)	(0.105)
ICT spillover (firm)	0.083**	0.086**	0.081**	0.082**	0.086**	0.079*	0.081**	0.081*
	(0.041)	(0.042)	(0.040)	(0.041)	(0.042)	(0.041)	(0.041)	(0.041)
Employees		0.052**						0.042
		(0.026)						(0.027)
Age			0.129*					0.118*
			(0.071)					(0.069)
Group (categorical)				-0.001				-0.001
				(0.001)				(0.001)
Intangible investment ratio					0.047			0.047
					(0.046)			(0.046)
Liquidity ratio						-0.011		0.013
						(0.095)		(0.095)
Mark-up							0.026	0.032
							(0.059)	(0.060)
Obs.	3,272	3,272	3,272	3,272	3,272	3,272	3,272	3,272
alpha	0.662	0.661	0.675	0.662	0.663	0.647	0.650	0.645
Log-likelihood	-1227	-1225	-1224	-1227	-1226	-1226	-1227	-1219
Pseudo R-squared	0.260	0.261	0.261	0.260	0.260	0.260	0.260	0.265

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

group of ICT producers (92 companies). The idea is to verify whether these firms are the sole capable of exploiting the cumulative advantage associated with earlier innovation in ICT, as captured by A_{ICT}, or benefit from spillover effect of ICT knowledge, as proxied by S_{ICT}. In estimates for the overall period 1995-2016 (col. (3)), the coefficient of ICT patent stock is insignificant suggesting that, apart from ICT producers, there are no dynamic returns induced by past innovation in this technology area. In the meantime, even non-ICT producers seem to gain from ICT-related knowledge spillovers (the parameter is 0.071). However, this pattern of results reverses when we focus on the period between 2009 and 2016 (col. (9)). Over this time frame, there is evidence of strong cumulativeness of innovation processes from the field of ICT to that of AI, whilst ICT spillover effects are not widespread but likely be confined to some sub-groups of companies. The second sectoral group omitted from the analysis is that of R&D sector companies (21 units). Being specialized on the development of new products, processes and services, these firms may have a differential patenting performance with respect to the rest of the sample. However, as estimates in cols. cols. (4) and (10) show, these firms do not appear to drive our general pattern of results.

Table 7: **Sample composition effects**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1995-2016						2009-2016					
AI patent stock	0.661***	0.697***	0.500***	0.701***	0.611***	0.326***	0.613***	0.595***	0.411***	0.657***	0.553***	0.247***
	(0.076)	(0.099)	(0.078)	(0.077)	(0.078)	(0.080)	(0.103)	(0.141)	(0.103)	(0.105)	(0.103)	(0.087)
ICT patent stock	0.085***	0.086**	0.017	0.075**	0.095***	0.106**	0.194***	0.192***	0.163***	0.183***	0.209***	0.219***
	(0.032)	(0.040)	(0.041)	(0.032)	(0.033)	(0.048)	(0.050)	(0.072)	(0.056)	(0.049)	(0.050)	(0.058)
AI inventive team	0.233**	0.205	0.093	0.211*	0.216*	0.284	0.259	0.177	0.082	0.206	0.265	0.257
	(0.116)	(0.143)	(0.156)	(0.121)	(0.130)	(0.188)	(0.166)	(0.198)	(0.222)	(0.170)	(0.191)	(0.285)
AI inventive collaborations	0.646	0.710	1.191*	0.686	0.711	0.187	1.211*	1.109	1.863*	1.210*	1.316*	0.877
	(0.534)	(0.514)	(0.661)	(0.536)	(0.536)	(0.723)	(0.708)	(0.685)	(1.057)	(0.684)	(0.727)	(1.501)
Tech specialisation	-0.227***	-0.367***	-0.190***	-0.229***	-0.194***	-0.203*	-0.091	-0.189	-0.100	-0.094	-0.053	-0.132
	(0.061)	(0.078)	(0.072)	(0.064)	(0.064)	(0.111)	(0.107)	(0.153)	(0.124)	(0.113)	(0.111)	(0.168)
AI maturity (dummy)	-2.342***	-2.638***	-2.508***	-2.414***	-2.368***	-2.637***	-2.197***	-2.281***	-2.489***	-2.125***	-2.238***	-2.569***
	(0.073)	(0.092)	(0.081)	(0.071)	(0.072)	(0.076)	(0.112)	(0.137)	(0.129)	(0.102)	(0.112)	(0.126)
ICT spillover (firm)	0.074***	0.103***	0.071**	0.080***	0.030	0.019	0.083**	0.108**	0.037	0.086**	0.032	0.033
	(0.027)	(0.033)	(0.030)	(0.027)	(0.027)	(0.029)	(0.041)	(0.051)	(0.050)	(0.040)	(0.043)	(0.045)
Excluding		Germany	ICT sector	R&D sector	Top 1	Top 10		Germany	ICT sector	R&D sector	Top 1	Top 10
Obs.	8,998	6,534	6,908	8,514	8,976	8,778	3,272	2,376	2,512	3,096	3,264	3,192
Firms	409	297	314	387	408	399	409	297	314	387	408	399
alpha	0.921	0.879	0.904	0.794	0.926	0.603	0.662	0.668	0.608	0.534	0.650	0.392
Log-likelihood	-2920	-2015	-2149	-2672	-2853	-2414	-1227	-894.4	-885.9	-1134	-1200	-1008
Pseudo R-squared	0.258	0.288	0.267	0.274	0.254	0.256	0.260	0.272	0.273	0.269	0.255	0.263

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

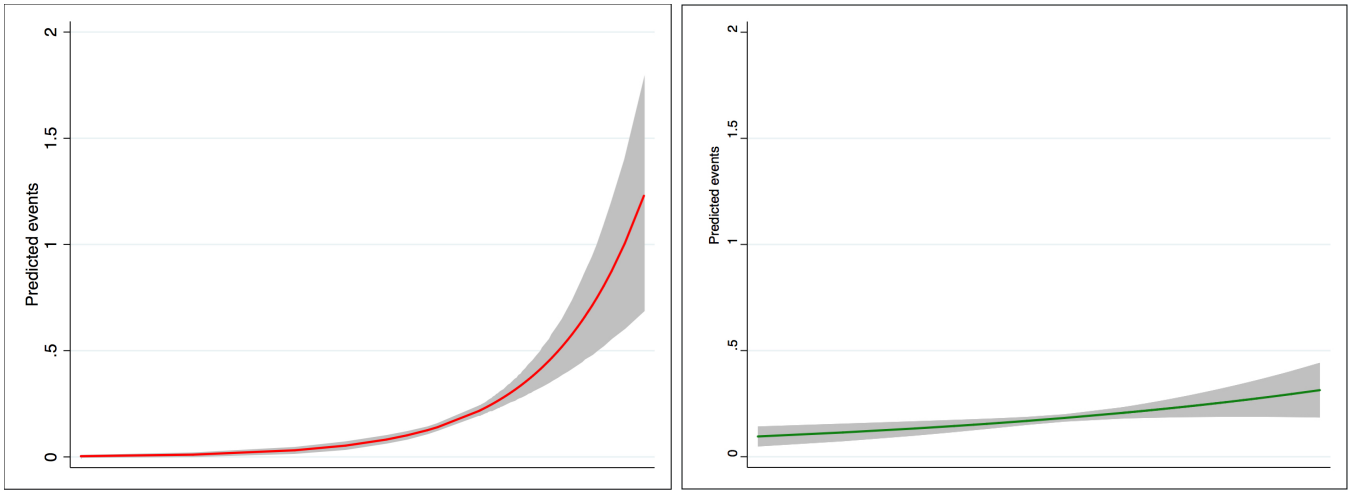
Lastly, we assess the incidence of the performance of AI frontier firms on our estimates. As known, the distribution of patenting companies is highly skewed and hence one may wonder whether companies at the top tail are driving the results. Therefore, we exclude from the sample the most prolific performers in each of the two time intervals, namely top 1 and top 10 applicants. Compared to our benchmark results (cols. (1) and (7)), neither ICT spillover nor the AI inventive team variable are significant in such regressions, suggesting that only top innovators are the most likely to benefit from geographical spillovers from ICT and return from own research in AI. Also, excluding the first ten most productive

firms, the magnitude of inter-temporal (within-firm) knowledge spillovers associated with AI patenting is much smaller, roughly the half than arising for the overall sample (0.326 in col. (6), and 0.247 in col. (12)).

Figure 2 plots the marginal effects associated with the stock of AI and ICT patents based on estimates for the period 1995-2016 (col. 1, Table 7), expressed in terms of predicted number of AI patents. The graphs illustrate thus how inter-temporal (within-firm) knowledge spillovers, enabled by the learning process associated with past innovations created in such technological fields, change along the distribution of the explanatory variables. The figure illustrates that until the mean value of the distribution, the marginal effect of ICT patent stock is quantitatively larger than that of AI patent stock, with a patent premium of 0.2-0.3 additional counts. However, as long as we move towards the upper tail of the distribution, the marginal effect associated with A_{AI} grows exponentially, from 0.1 additional patents at the mid-distribution to 1.3 patents at the top distribution. This gives clear indication on the strong cumulativeness of returns to innovation for top innovators, whose technological lead (and market power) self-enforces as a result of their success in AI patenting.

Figure 2: **Inter-temporal (within-firm) knowledge spillovers: Marginal effects** (1995-2016)

(a) AI patent stock (A_{AI}) (b) ICT patent stock (A_{ICT})



Notes: Marginal effects of A_{AI} and A_{ICT} (in logs) based on estimates in col. 1, Table 7.

Additional robustness checks

Finally, we summarize the results yielded by a wider set of robustness checks conducted to further assess the sensitivity of estimates. For sake of brevity, these regression results are summarized here and are reported in the Online Appendix.

Innovation quality measurement. To understand whether our findings are influenced by the nature of the patent indicator used, in the Online Appendix Table A.4 we conduct a widely comprehensive analysis

and estimate our model using patent variables adjusted for all possible quality indicators made available in the OECD Patent Quality Indicators database (see Squicciarini et al., 2013). The set of patent quality indicators ensuring convergence of the negative binomial regression includes: patent scope, family size, grant lag, backward cites, non-patent literature cites, claims, backward cites per claim, forward cites (5 year window), forward cites (7 year window), breakthrough, originality, radicalness, renewal. In such robustness checks, the coefficient of the AI patent stock is much more stable than the parameter of ICT patent stock, being the former significant and with the expected sign in 12 out 13 regressions, against 7 cases for the latter. In terms of magnitude, the coefficients of the firm stock of AI and ICT patents, obtained using raw patent counts as a measure of innovation output, fall roughly in the midst of the values obtained using quality-adjusted patent indicators. On this basis, our benchmark estimates in col. (1) can be considered sufficiently conservative in the assessment of inter-temporal (within-firm) knowledge spillovers (learning effects).

Nature of (external) knowledge spillovers. In Online Appendix Table A.5 we extensively explore how the transmission of knowledge from geographically continuous inventive units affect the patent productivity of AI innovators, distinguishing the institutional nature of the knowledge sources, namely business companies, public research institutions and individual inventors.[17] These estimates yield two unambiguous results: first, there is no spillover effect associated with the inventive activity of public research institutions and individual inventors and, second, the only significant effect is the spillover enabled by the innovations developed by the business sector in the field of ICT. The absence of cross-firm spillovers from AI innovation may be related to the high tacitness of underlying knowledge and the high costs to entry the field, relatively to ICT. AI technologies are intangible in nature and research activities necessary to their implementation are more easily scalable from large firms (De Ridder, 2019, Corrado et al., 2021). This is consistent with our evidence on the strong dynamic returns of AI patenting, contributing to explain why first movers grow large and gain a huge market power, are geographically concentrated and do not source spillovers. These characteristics could make AI different from previous breakthrough technologies as ICT and in turn affect the concentration process of the world's market for the new technology. Note that similar results emerge even when we adopt alternative weighting schemes in the construction of the geographical spillover variable, namely an exponential distance decay scheme with a spillover parameter that halves every 200 kilometers (Lychagin et al., 2016), and a variant of our linear distance matrix that forces spillovers to vanish within a radius of 50 and 100 kilometers (Acs et al., 2002). Results are unreported but are available upon request.

Econometric issues. Finally, we evaluate the stability of results to the econometric method used. Firstly, we assess the impact on estimates of the massive incidence of zeros in the dependent variable and hence we re-estimate the model with the zero-inflated negative binomial regression, where the zeroes are explained with the pre-sample mean values of AI patents. Secondly, we explicitly model the panel

[17] The nature of the applicant has been identified through an accurate procedure of name disambiguation, based on tokenization of the main keywords (for instance university, council, etc) translated in different languages. The quality of the match has been checked ex post in order to exclude false positives.

structure of our data and run the pseudo-fixed effects model. The findings of these regressions are shown in the Online Appendix Table A.6. In both sets of regressions, the impact of the explanatory variable does not differ much from the pre-sample fixed effects model. It makes exception only the the stock of AI patents, which remains highly significant but with a parameter smaller than found thus far, especially over the longer time interval (0.131 in col. 3 and 0.333 in col. 6). This result, however, is not un-expected as the propensity to patent is a characteristic largely idiosyncratic to the nature of the firm (and hence it is highly persistent).

In Table A.7, we estimate the regression model explicitly reformulated as a dynamic specification, i.e. including the one-year lag of the dependent variable as regressor (and taking the AI patent stock with a two-year lag). Results show that there is high persistency in AI innovative processes over the long time horizon, but less since 2009. Indeed, in the latter time interval, the lagged dependent variable loses significance, indicating the technology race has become fiercer or more complex, and hence returns to internal knowledge (i.e., inter-temporal within-company spillovers) take more time to show up, noting that the AI patent stock is still highly significant and economically important.

An open issue in our regression framework is the possible reverse causality existing between the dependent variable and the regressors. Firms may strategically decide to patent in AI by anticipating, for instance, a future increase in their chances to undertake technological collaborations, to benefit from greater research returns, or access larger external knowledge. However, for the main aim of this paper, which is the measurement of the inter-temporal (within-firm) knowledge spillovers in AI production, estimation bias induced by simultaneity feedbacks are likely to be less relevant as the variable approximating the learning effects consists in the cumulative value of AI innovations developed in the past. Hypothetically, firms may decide to patent in AI as expecting greater inter-temporal knowledge spillovers but, however, this would itself reflect dynamic returns in such patenting activities. All this makes it is hard to find credible external instruments that are correlated with the AI patent stock (relevance condition) and, in the meantime, are uncorrelated with AI patent counts (orthogonality condition).

4.2.3 Identification of the mechanisms and quantification of the effects

Finally, we recover the theoretical parameters featuring the knowledge production function (eqs. (2)-(4)), and discuss more carefully the strength of the mechanisms at work. Based on all estimates produced for the period 1995-2016, the average value of the coefficient of the AI patent stock, γ_1, amounts to 0.60 and that of the ICT patent stock, γ_2, to 0.13. Our estimates would therefore indicate that the share of the AI patent stock on the internal knowledge pool, θ, would be equal to 0.82,[18] and in turn that the elasticity of inter-temporal (within-firm) spillovers, ϕ, would be 0.72.[19] For the pool of external knowledge, the average value of the inter-firm spillover parameter, ζ, across regressions is 0.07, due to the fact that the ICT patent stock is the only significant spillover source $(1 - \vartheta = 1)$.[20]

[18] $\theta = (\widehat{\gamma}_1/\widehat{\gamma}_2)/(1 + (\widehat{\gamma}_1/\widehat{\gamma}_2)) = (0.60/0.13)/(1 + (0.60/0.13))$.

[19] $\phi = \widehat{\gamma}_1/\theta = 0.60/0.82$ or equivalently $\phi = \widehat{\gamma}_2/(1 - \theta) = 0.13/(1 - 0.82)$.

[20] This finding derives from the insignificance of inter-firm AI spillover as of col. 5, Table 4, $\gamma_3 = \zeta\ \vartheta = 0\ (\rightarrow \vartheta = 0)$.

Returns to research input, σ, amount to 0.23 as average across regressions (albeit not always significant), falling close to the values reported in earlier works (Ang and Madsen, 2011, Venturini, 2012, 2015). The coefficient of firm size, L, in Table 6 corresponds to the parameter of product proliferation, ϱ. This elasticity is positive and hence conflicts with the predictions of the theory concerning the dilution of research effort across expanding product varieties. Taken rigorously, this finding would suggest that firms developing AI technologies can easily exploit their research output over a large range of product types, in this respect explaining the rapid diffusion of AI-intensive goods and services as documented by Nakazato and Squicciarini (2021).

Overall, our findings emphasize the importance of dynamic returns in the creation of the new technology and that the advantage of the firms at the frontier of AI greatly depends on internal (built-up) competences. Our estimate for ϕ (0.72) suggests that a one-unit difference in the patent stock of AI (and ICT) between two companies in a given year would translate into a three-unit difference after ten years. This finding would prove the self-enforcing lead that early movers acquire over late comers in the AI market.

5 Concluding remarks

This paper has investigated the nature of European firms innovating in AI and which factors drive their patent productivity. We have illustrated that AI innovation has been undertaken by the most prolific firms innovating in the field of ICT. In developing this generation of new technologies, European firms have taken advantage of strong dynamic returns, by sizeably learning from innovations developed in the past in this area and in the technologically contiguous field of ICT, especially in network and communication technologies, high-speed computing and data analysis, and more recently in cognition and imaging. In the long run, patent productivity of AI companies has been higher for those with a larger research effort, as proxied by AI inventive team, and lower for those with a greater maturity and narrowness of technological competencies on the field. AI inventing companies have also benefited from inter-firm ICT knowledge spillovers; this effect, however, is confined to a smaller group of top innovators. The results of our analysis suggest that there is a small group of top innovators at the frontier of AI, which exploit their first-move advantage, as well as built-up competencies, to strengthen their technological leadership and expand their market power.

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The determinants of AI innovation across European firms: Online Appendix

Ioana Igna Francesco Venturini*

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A.1 - Descriptive analysis

Table A.1 **List of countries**

		Probit sample		KPF sample	
		Freq.	Percent	Freq.	Percent
1	AT	521	2.6	18	4.4
2	BE	521	2.6	10	2.4
3	BG	17	0.1	0	0.0
4	CH	29	0.1	23	5.6
5	CY	51	0.3	0	0.0
6	CZ	47	0.2	1	0.2
7	DE	5,261	26.1	112	27.4
8	DK	555	2.7	6	1.5
9	EE	36	0.2	0	0.0
10	ES	292	1.4	20	4.9
11	FI	824	4.1	16	3.9
12	FR	2,885	14.3	56	13.7
13	GB	3,986	19.7	52	12.7
14	HU	62	0.3	0	0.0
15	IE	442	2.2	2	0.5
16	IT	1,526	7.6	42	10.3
17	LI	41	0.2	0	0.0
18	LU	187	0.9	1	0.2
19	LV	10	0.0	0	0.0
20	MT	25	0.1	0	0.0
21	NL	1,058	5.2	30	7.3
22	NO	2	0.0	2	0.5
23	PL	164	0.8	5	1.2
24	PT	41	0.2	1	0.2
25	RO	11	0.1	0	0.0
26	SE	1,231	6.1	10	2.4
27	SI	36	0.2	0	0.0
28	SK	11	0.1	0	0.0
29	TR	2	0.0	2	0.5
	Unassigned	318	1.6	0	0.0
	TOTAL	20,192	100.0	409	100.0

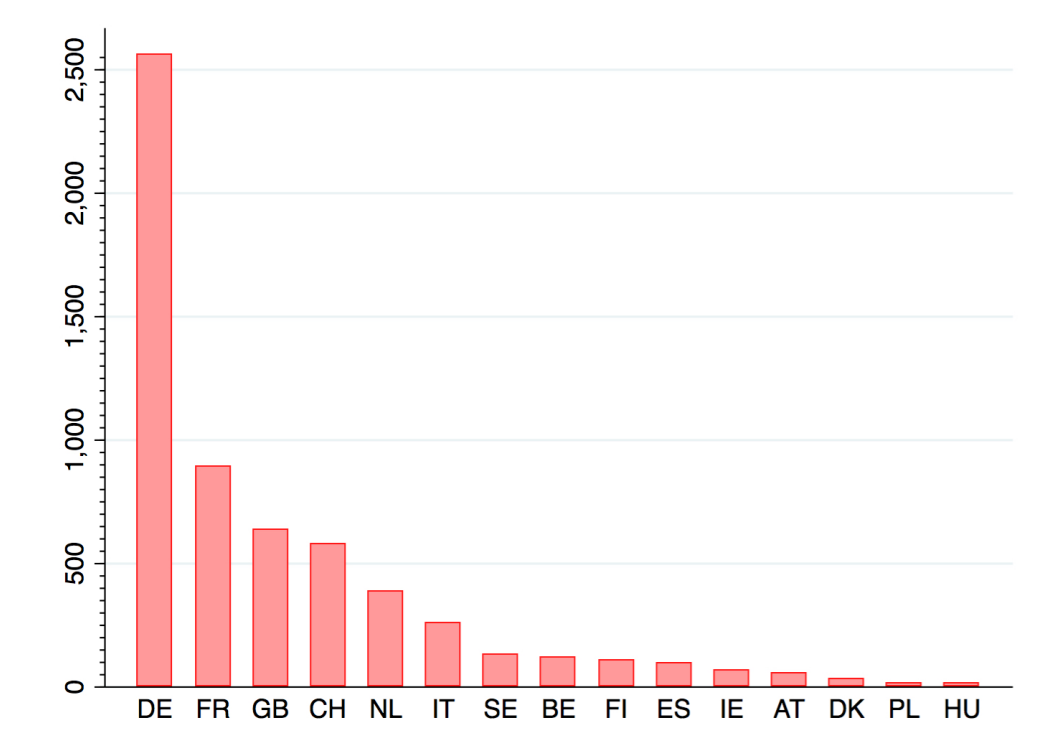
*Ioana Igna: Department of Business Administration, Lund University (SE). Francesco Venturini: Department of Economics, University of Perugia (Perugia, IT) and NIESR (London, UK). Corresponding author: francesco.venturini@unipg.it. Via Pascoli 20, 06123 Perugia (IT).

Table A.2 **List of variables**

Probit variables	**Type**	**Description**
ICT patenting	dummy	Firm with at least one patent application in the fields of ICT
Small portfolio	dummy	Applicant with a total number of patent applications bellow 25% of the ICT distribution
Medium-small portfolio	dummy	Applicant with a total number of patent applications between 25 and 50% of the ICT distribution
Medium-large portfolio	dummy	Applicant with a total number of patent applications between 50 and 75% of the ICT distribution
Large portfolio	dummy	Applicant with a total number of patent applications above 75% of the ICT distribution
ICT patent stock	continuous	Cumulative number of ICT patent applications
Age	continuous	Number of years from the first patent application
Technlogical specialisation	share	Herfindahl-Hirschman concentration index of technological classes covered by the company's patents
Technological breadth	continuous	Number of prior arts claimed in the patent document
Industry	dummy	6 main categories NACE Rev.2
KPF variables		
AI /ICT patent stock	continuous	Cumulative number of AI / ICT patent applications
Technological specialisation	share	Herfindahl-Hirschman concentration index of technological classes covered by the company's patents
AI inventive team	continuous	Number of (disambiguated) inventors included in the AI patent application
AI collaborations	continuous	Number of AI collaborations (co-patenting)
AI maturity	dummy	Companies with a number of years from the first AI application greater than the median of the distribution
AI / ICT spillover	continuous	Inverse-distance weighted average of AI/ ICT patent stocks of donor units (business companies, public research institutions, individual inventors)
Size	continuous	Number of employees
Age	continuous	Number of years from the establishment
Group	categorical	Affiliation to the same business group
Asset intangibility	continuous	Ratio of intangibles to total fixed investments
Liquidity ratio	continuous	Debts over current liabilities
Mark-up	continuous	Ratio between operating profits and net sales
Industry	dummy	44 Categories NACE Rev.2

Figure A.1 **Total AI and ICT patents by country** (1995-2016)

(a) AI patents (> 10)



(b) ICT patents (> 1000)

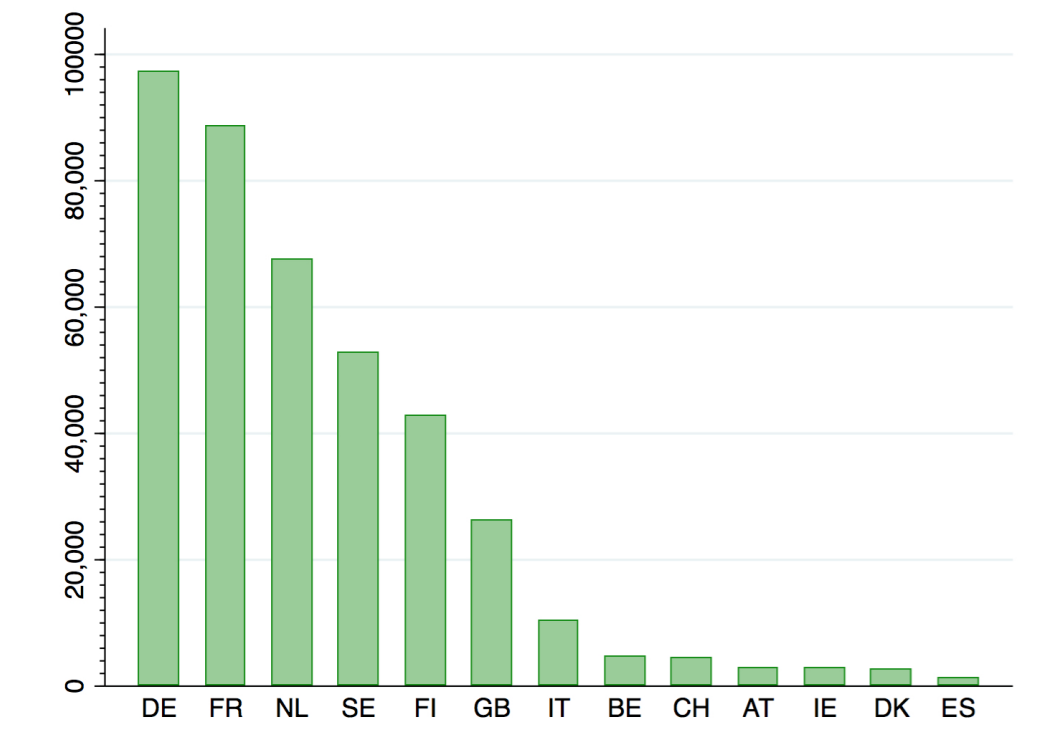


Table A.3 **Full Summary statistics** (409 firms, 1995-2016 and 2009-2016)

	1995-2016		2009-2016	
	Mean	SD	Mean	SD
AI patents	0.16	0.60	0.20	0.67
Technological characteristics				
AI patent stock	0.81	2.06	1.07	2.31
ICT patent stock	32.1	190.5	47.4	249.2
AI inventive team	3.21	3.14	3.49	3.60
AI collaborations	0.01	0.10	0.01	0.12
Tech specialisation	0.68	0.69	0.73	0.77
AI maturity	0.87	0.34	0.83	0.37
Knowledge spillovers				
AI spillover (total)	3.35	8.74	4.26	11.36
AI spillover (firm)	3.19	8.67	4.06	11.28
AI spillover (public research inst.)	0.08	0.35	0.14	0.52
ICT spillover (total)	500.5	1760.9	687.3	2104.0
ICT spillover (firm)	255.2	1213.0	357.6	1606.7
ICT spillover (public research inst.)	13.54	51.14	23.00	75.44
Structural characteristics				
Employees			9392	42625
Age			31.50	32.76
group			0.60	0.49
Asset intangibility			0.15	0.26
Liquidity ratio			2.42	6.87
Mark-up			0.07	1.75

A.2 - Robustness checks for knowledge production function estimates

Table A.4: **Baseline estimates with patent quality adjustment** (409 firms, 1995-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
AI patent stock	0.678***	0.312***	0.357***	0.247***	0.363***	0.097	0.236***	0.294***	0.539***	0.466***	0.685***	0.551***	0.622***	0.235***
	(0.077)	(0.069)	(0.071)	(0.045)	(0.059)	(0.102)	(0.056)	(0.075)	(0.069)	(0.070)	(0.083)	(0.073)	(0.082)	(0.065)
ICT patent stock	0.083**	0.144***	0.147***	0.459***	0.185***	0.118*	0.193***	0.267***	0.038	0.091	-0.126**	-0.067	-0.125**	0.251***
	(0.032)	(0.055)	(0.054)	(0.041)	(0.057)	(0.067)	(0.050)	(0.061)	(0.059)	(0.056)	(0.062)	(0.057)	(0.063)	(0.054)
AI inventive team	0.251**	0.240	0.193	-0.459	0.152	0.185	0.068	0.433**	0.391**	0.440***	0.275***	0.329***	0.274**	0.113
	(0.116)	(0.151)	(0.168)	(0.434)	(0.174)	(0.158)	(0.188)	(0.172)	(0.157)	(0.162)	(0.106)	(0.124)	(0.113)	(0.165)
AI collaborations	0.562	0.480	0.123	-2.372	0.569	0.968	0.522	0.050	0.150	0.269	0.687	0.606	0.803	0.949
	(0.529)	(0.775)	(0.725)	(1.670)	(0.804)	(0.629)	(0.939)	(0.761)	(0.539)	(0.587)	(0.427)	(0.623)	(0.496)	(0.958)
Tech specialisation	-0.223***	-0.113	-0.122*	0.273*	-0.030	-0.304***	-0.050	-0.160**	-0.177**	-0.154**	-0.227***	-0.193***	-0.228***	-0.096
	(0.061)	(0.074)	(0.074)	(0.155)	(0.084)	(0.088)	(0.088)	(0.079)	(0.074)	(0.076)	(0.057)	(0.070)	(0.063)	(0.087)
AI maturity (dummy)	-2.347***	-3.424***	-3.916***	-9.409***	-3.968***	-3.252***	-4.798***	-3.596***	-2.605***	-2.758***	-2.232***	-2.585***	-2.293***	-4.116***
	(0.073)	(0.078)	(0.093)	(0.266)	(0.096)	(0.095)	(0.114)	(0.099)	(0.072)	(0.076)	(0.067)	(0.059)	(0.059)	(0.102)
Quality adjustment	NO	Patent scope	Family size	Grant lag	Backward cites	Non-patent literature cites	Claims	Backward cites per claim	Forward cites (5 year window)	Forward cites (7 year window)	Break-through	Original-ity	Radical-ness	Renewal
Obs.	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998	8,998
alpha	0.944	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103
Log-likelihood	-2923	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8	-439.8
Pseudo R-squared	0.257	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean company fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: **Spillover effects by knowledge sources and over time** (409 firms, 1995-2016 and 2009-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1995-2016						2009-2016					
AI patent stock	0.671***	0.670***	0.673***	0.667***	0.661***	0.668***	0.627***	0.627***	0.629***	0.622***	0.613***	0.622***
	(0.077)	(0.077)	(0.077)	(0.077)	(0.076)	(0.077)	(0.105)	(0.104)	(0.104)	(0.104)	(0.103)	(0.103)
ICT patent stock	0.084***	0.084***	0.084***	0.084***	0.085***	0.086***	0.189***	0.189***	0.190***	0.191***	0.194***	0.193***
	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
AI inventive team size	0.243**	0.243**	0.246**	0.240**	0.233**	0.240**	0.278*	0.276*	0.282*	0.275*	0.259	0.273*
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.164)	(0.164)	(0.166)	(0.165)	(0.166)	(0.166)
AI collaborations	0.593	0.595	0.571	0.623	0.646	0.607	1.149	1.153	1.137	1.180*	1.211*	1.185*
	(0.535)	(0.534)	(0.533)	(0.535)	(0.534)	(0.534)	(0.711)	(0.710)	(0.712)	(0.709)	(0.708)	(0.716)
Tech specialisation	-0.222***	-0.222***	-0.224***	-0.226***	-0.227***	-0.227***	-0.088	-0.088	-0.090	-0.089	-0.091	-0.093
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.106)	(0.106)	(0.106)	(0.106)	(0.107)	(0.107)
AI maturity (dummy)	-2.344***	-2.344***	-2.347***	-2.343***	-2.342***	-2.342***	-2.190***	-2.191***	-2.188***	-2.189***	-2.197***	-2.189***
	(0.072)	(0.072)	(0.073)	(0.073)	(0.073)	(0.072)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)
AI spillover (total)	0.049						0.037					
	(0.034)						(0.051)					
AI spillover (firm)		0.051						0.042				
		(0.033)						(0.051)				
AI spillover (public research inst.)			0.018						0.021			
			(0.030)						(0.046)			
ICT spillover (total)				0.057*						0.052		
				(0.029)						(0.045)		
ICT spillover (firm)					0.074***						0.083**	
					(0.027)						(0.041)	
ICT spillover (public research inst.)						0.035						0.042
						(0.024)						(0.035)
Obs.	8,998	8,998	8,998	8,998	8,998	8,998	3,272	3,272	3,272	3,272	3,272	3,272
alpha	0.933	0.933	0.941	0.933	0.921	0.933	0.670	0.669	0.674	0.672	0.662	0.669
Log-likelihood	-2922	-2922	-2923	-2921	-2920	-2922	-1229	-1229	-1229	-1228	-1227	-1229
Pseudo R-squared	0.258	0.258	0.257	0.258	0.258	0.258	0.259	0.259	0.259	0.259	0.260	0.259

Notes: Negative Binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean company fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6 **Estimates using alternative regression methods** (409 firms, 1995-2016 and 2009-2016)

	(1)	(2)	(3)	(4)	(5)	(6)
		1995-2016			2009-2016	
AI patent stock	0.661***	0.720***	0.131**	0.613***	0.617***	0.333***
	(0.076)	(0.073)	(0.061)	(0.103)	(0.103)	(0.082)
ICT patent stock	0.085***	0.095***	0.228***	0.194***	0.211***	0.231***
	(0.032)	(0.032)	(0.041)	(0.050)	(0.048)	(0.054)
AI inventive team	0.233**	0.232*	0.074	0.259	0.250	-0.036
	(0.116)	(0.119)	(0.092)	(0.166)	(0.165)	(0.137)
AI collaborations	0.646	0.476	0.699	1.211*	1.133	1.186
	(0.534)	(0.512)	(0.575)	(0.708)	(0.692)	(0.723)
Tech specialisation	-0.227***	-0.233***	-0.141***	-0.091	-0.064	-0.125
	(0.061)	(0.060)	(0.052)	(0.107)	(0.102)	(0.090)
AI maturity	-2.342***	-2.313***	-3.808***	-2.197***	-2.133***	-3.091***
	(0.073)	(0.072)	(0.122)	(0.112)	(0.107)	(0.175)
ICT spillover (firm)	0.074***	0.055**	0.054	0.083**	0.073*	0.081
	(0.027)	(0.026)	(0.053)	(0.041)	(0.041)	(0.063)
Pre-sample mean		-1.012**			-15.326***	
		(0.410)			(2.079)	
Estimator	Negative binomial	Zero-inflated Negative binomial	Within fixed effects	Negative binomial	Zero-inflated Negative binomial	Within fixed effects
Obs.	8,998	8,998	8,998	3,272	3,272	3,272
alpha	0.921			0.662		
Log-likelihood	-2920	-2935	-2647	-1227	-1230	-1167
Pseudo R-squared	0.258			0.260		

Notes: Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7 **Estimates from the dynamic specification** (409 firms, 1995-2016 and 2009-2016)

	(1)	(2)	(3)	(4)
	1995-2016		2009-2016	
AI patents (one-year lagged)	0.620***	0.594***	0.070	0.021
	(0.195)	(0.194)	(0.232)	(0.234)
AI patent stock (two-year lagged)	0.567***	0.569***	0.609***	0.600***
	(0.073)	(0.072)	(0.103)	(0.102)
ICT patent stock	0.104***	0.094***	0.179***	0.184***
	(0.033)	(0.032)	(0.048)	(0.048)
AI inventive team	-0.072	-0.050	0.273	0.280
	(0.161)	(0.160)	(0.197)	(0.198)
AI collaborations	0.492	0.604	1.626***	1.715***
	(0.476)	(0.460)	(0.619)	(0.624)
Tech specialisation	-0.195***	-0.207***	-0.098	-0.101
	(0.063)	(0.063)	(0.106)	(0.106)
AI maturity (dummy)	-2.363***	-2.350***	-2.213***	-2.218***
	(0.072)	(0.072)	(0.116)	(0.117)
AI spillover (firm)	0.045		0.040	
	(0.033)		(0.049)	
ICT spillover (firm)		0.066**		0.084**
		(0.027)		(0.039)
Patent indicator	Counts	Counts	Counts	Counts
Knowledge obsolescence	15%	15%	15%	15%
Pre-sample	Yes	Yes	Yes	Yes
Obs.	8,998	8,998	3,272	3,272
alpha	0.888	0.899	0.602	0.591
Log-likelihood	-2913	-2917	-1225	-1223
Pseudo R-squared	0.260	0.259	0.261	0.262

Notes: Negative binomial estimates. Dep. variable: Number of AI patents. All estimates include pre-sample mean fixed effects, 2-digit NACE industry fixed effects, and time dummies. Standard errors clustered at firm level and over time. Except for *AI maturity* (dummy variable), all regressors are in logs and one-year lagged w.r.t. the dependent variable. AI patent stock is two-year lagged. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$