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ABSTRACT

The Knowledge Spillover Theory of Entrepreneurship and Innovation (KSTE+I) Approach and the Advent of AI Technologies: Evidence from the European Regions*

In this paper we integrate the insights of the Knowledge Spillover Theory of Entrepreneurship and Innovation (KSTE+I) with Schumpeter's idea that innovative entrepreneurs creatively apply available local knowledge, possibly mediated by Marshallian, Jacobian and Porter spillovers. In more detail, in this study we assess the degree of pervasiveness and the level of opportunities brought about by AI technologies by testing the possible correlation between the regional AI knowledge stock and the number of new innovative ventures (that is startups patenting in any technological field in the year of their foundation). Empirically, by focusing on 287 Nuts-2 European regions, we test whether the local AI stock of knowledge exerts an enabling role in fostering innovative entry within AI-related local industries (AI technologies as focused enablers) and within non AI-related local industries, as well (AI technologies as generalised enablers). Results from Negative Binomial fixed-effect and Poisson fixed-effect regressions (controlled for a variety of concurrent drivers of entrepreneurship) reveal that the local AI knowledge stock does promote the spread of innovative startups, so supporting both the KSTE+I approach and the enabling role of AI technologies; however, this relationship is confirmed only with regard to the sole high-tech/ AI-related industries.

JEL Classification: O33, L26

Keywords: KSTE+I, Artificial Intelligence, innovative entry, enabling technologies

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1. Introduction

As with previous instances of real or perceived technological revolutions, the advent of a new technology such as Artificial Intelligence (AI) inevitably raises concerns regarding its initial impact on employment and the society at large. Indeed, it is not uncommon for the emergence of an extremely new and pervasive technology to elicit more fears than hopes, sometimes leading to an overemphasis on its short-term negative implications rather than the long-term benefits of the structural changes it might bring about. However - at the current stage of the debate - the implications of AI are undetermined, leaving policymakers unable to envisage proper policies for the future.

Although the academic debate is currently focusing on these general issues, the scope of this paper is different, as it addresses a novel and still unexplored research question. In particular, this study aims to investigate the tangible impact of AI knowledge as a catalyst for entrepreneurial activity centred around this technology. Our analysis focuses on the Nuts-2 European regions, a level of investigation that many scholars have identified as a viable proxy for the Entrepreneurial Ecosystem (Stam, 2015; Sussan and Acs, 2017; Lafuente et al., 2022). From a conceptual viewpoint, we integrate the insights of the Knowledge Spillover Theory of Entrepreneurship and Innovation (henceforth KSTE+I) - put forward by the seminal contribution of Acs et al. (2009) - with Schumpeter's idea that innovative entrepreneurs apply and transform available local knowledge. By doing so, we aim to provide a more in-depth understanding of how AI-driven knowledge spillovers can be associated with the widespread emergence of innovative firms in turn exploiting AI-based knowledge and therefore potentially mitigate some of the negative labor market impacts historically associated with technological revolutions. Indeed, innovative entrepreneurship has been demonstrated to exhibit a higher likelihood of survival and better occupational prospects compared to imitative (or even "defensive") entrepreneurship (Lotti et al., 2003).

Our approach not only extends the theoretical framework of KSTE+I but also situates it within the contemporary discourse on AI and its economic and social impacts. In particular, the empirical evidence presented in the subsequent sections of this paper indicates the presence of a virtuous interaction between knowledge creation and knowledge exploitation, facilitated by the dynamic interplay of spillovers and the formation of innovative firms.

The paper is organised as follows. Section 2 provides a conceptual framework, placing particular emphasis on studies that have expanded upon the original Schumpeterian framework. Section 3 details the methodological approach used to develop the unique dataset employed for the empirical analysis. Section 4 outlines the econometric strategy. Section 5 provides a discussion of the empirical results, while Section 6 briefly concludes.

2. Theoretical setting

Ever since Joseph Schumpeter ([1911] 1934, 1939), there has been a widespread consensus on the role of innovation and the entrepreneur as a disturbance actor: contrary to Kirzner's arguments (1973, 1997), a Schumpeterian formulation of entrepreneur encompasses a subject, who turns inventions (knowledge) into innovations (economic, exploitable knowledge), triggering a process of "creative destruction" (Aghion & Howitt, 1992) and economic growth (Audretsch et al., 2006; Acs et al., 2009; Braunerhjelm et al., 2010). In this context, young, knowledge-intensive and innovative firms (Malerba & McKelvey, 2020) can be seen as playing the main role in the entrepreneurial process: by introducing dynamism and new technologies onto the market, they foster competition and, displacing inefficient firms, they trigger a selection mechanism. By the same token, this subset of new entrants is the main responsible for the emergence of new sectors (therefore, opportunities), wealth and job creation, net of any business stealing effect (Piva & Vivarelli, 2005; Decker et al., 2014; Damsgaard et al., 2017). In this vein, technological revolutions - as was the case of ICTs in the late decades of the past century and AI nowadays - the emergence of new sectors and innovative entry rates are highly correlated phenomena.

2.1. The KSTE+I and the role of geographical proximity

In describing the entrepreneurial process, an important contribution is provided by the Knowledge Spillover Theory of Entrepreneurship and Innovation (Acs et al., 2009; Carlsson et al, 2009, Braunerhjelm et al., 2010; Audretsch and Belitski, 2013): this theory represents a significant advancement in economic thought, building upon the foundations laid by Solow's Total Factor Productivity (TFP) Model (1956), Griliches' (1984) Knowledge Production Function (KPF) approach, and Romer's (1990) Theory of Endogenous Growth (TEG). At its core, the Knowledge Spillover Theory of Entrepreneurship and Innovation (KSTE+I) enriches these theories by integrating the pivotal role of entrepreneurship in the transformation of potential commercially valuable knowledge into economically viable assets, thereby adding the "missing link" on knowledge spillovers between economic agents.

Similar to its predecessors, KSTE+I operates under the premise that technological progress and knowledge accumulation serve as primary engines of economic advancement. However, it distinguishes itself by offering a comprehensive although indirect account of how TFP growth, which quantifies output increases resulting from improved production methods while holding inputs constant, leads to accelerated economic growth through new firm formation. Thus, the KSTE+I adds a Schumpeterian flavour to the analysis of economic growth and structural change, by incorporating in the theoretical framework the function of innovative (creative) entrepreneurship.

In the KSTE+I, in line with Schumpeter's ([1911] 1934) view of innovation as a "disruptive force" and the entrepreneur as a "factor of disequilibrium", technological breakthroughs are particularly advantageous for industries marked by a greater endowment of entrepreneurial capital. This is because new entrepreneurial ventures serve as catalysts for change, facilitating the utilization of knowledge generated but not directly exploited by established incumbents and academic institutions. Therefore, the creation of new innovative firms is assumed to be an "endogenous and creative response" to knowledge and opportunities generated within a given location (Acs et al., 2013; Antonelli & Colombelli, 2023; Colombelli et al., 2024).

In essence, the KSTE+I not only enhances our understanding of economic growth but also underscores the critical role of entrepreneurial endeavours in harnessing the full potential of emerging knowledge and inventions for the prosperity of countries and regions.

However, the process of translating research findings (inventions) into commercially viable knowledge (innovations) encounters substantial obstacles, which Carlsson et al. (2009) define as the "knowledge filter." Moreover, the entire process is characterized by Knightian uncertainty (Knight, 1921; Audretsch & Belitski, 2021), implying that the nature and timing of the economic outcomes derived from knowledge are unknown ex-ante.

Therefore, in both academic and industrial spheres, the overarching challenge lies in bridging the gap between the creation of knowledge and its practical application in the marketplace; in overcoming the knowledge filter, spillovers play a crucial role. Indeed, nurturing the possibility that knowledge spillovers generated by either industrial R&D or university research are captured by new ventures with a strong inclination towards innovation and creativity represents the optimal solution if one desires that (almost) all the potentially available knowledge created by the various actors in a given ecosystem is effectively utilized (Audretsch and Belitski, 2013).

An in-depth comprehension of the mechanisms underpinning the exploitation of knowledge generated but not directly utilized by established firms and academic institutions by new innovative firms can be achieved by examining three principal theoretical frameworks pertaining to the dynamics of knowledge flows and spillovers. These frameworks underscore the significance of geographic and/or industry proximity in facilitating general knowledge flows. The first framework - rooted in the works of Alfred Marshall (1920), Kenneth Arrow (1962), and Paul Romer (1990) - accentuates that knowledge spillovers are more pronounced within the same industry and geographical region, thereby easing knowledge transfers and enabling the aggregation of skilled labor. The second framework, advocated by Jane Jacobs (1961), posits that knowledge emanating from diverse industries in close geographic proximity stimulates innovation and productivity growth within a region, leading to the formation of innovation hubs, in turn generating agglomeration externalities. The third framework, espoused by Michael Porter (1990) and consonant with the preceding two, contends that knowledge spillovers in specialized industries concentrated geographically propel growth through vigorous competition and continual advancements. Regardless of the preferred approach, geography does play a crucial role: indeed, knowledge flows - which constitute the precondition to knowledge spillovers - tend to be localized (Audretsch & Feldman, 1996).

In fact, the role of regions and places have been reassessed by the emergence of a stream of literature at the intersection of the KSTE+I and Entrepreneurial Ecosystem approaches: a lot of effort has been devoted to investigating the factors within Entrepreneurial Ecosystems (Stam, 2015) that spur, first of all, knowledge flows and, secondly, knowledge spillovers. Among all, critical factors are: the degree of diversity, both of industries but especially of people; the level of competition; the presence of an entrepreneurial and agency culture; the structure and density of the network connecting agents (that might further reinforce general knowledge flows); the presence of supportive institutions and laws (Carbonara et al., 2018; Qian, 2018; Morris et al., 2023); the degree of coherence and relatedness of the regional knowledge base (Colombelli & Quatraro, 2018).

In summary, both the regional and sectoral contexts are significant in the process that links the creation of new knowledge to the dissemination of a portion of it through spillovers, and ultimately to its utilization by entrepreneur-innovators who transform it into new products/services, or into more efficient processes.

2.2. The role of technology

The KSTE+I approach - while being illuminating in highlighting the channels and hindrances characterizing the localised spillover effects and the role of innovative startups - remains very general as far as technology is concerned. Technological breakthroughs, radical innovations or even changes in *technological paradigms* (Dosi, 1982 and 1988) can be seen as powerful triggers of spillovers and start-ups in industries and regions characterised by a greater endowment of potential entrepreneurial capital. Indeed, the emergence of new technologies might trigger new dynamism, particularly among individuals better endowed with entrepreneurial absorptive capacity exploiting these new opportunities (Qian & Acs, 2013). In sum, the explicative power of the KSTE+I approach in giving account of economic growth should be particularly pronounced when technological change accelerates, thereby increasing the technological stock which is recognized as the key engine of growth (Antonelli et al., 2023).

Recently, a theoretical debate has arisen, focusing on the characteristics of Artificial Intelligence and the so-called Fourth Industrial Revolution (4IR) technologies; specifically, this literature stream discusses whether or not the latter should be considered a general enabling factor (Chalmers et al., 2021; Shepherd & Majchrzak, 2022, Giuggioli & Pellegrini, 2022; Davidsson & Sufyan, 2023), a general-purpose technology (Obschonka & Audretsch, 2020; Eloundou, T., 2023) and a new technological revolution (Rifkin, 2011; Schwab, 2017; Cetrulo & Nuvolari, 2019; Lee & Lee, 2021; Santarelli et al., 2023).

More in particular, Artificial Intelligence is thought to be "*the next GPT*" (Trajtenberg, 2019) because of its high pervasiveness throughout the entire economy and versatility, thus enabling the creation of an ecosystem of complementary innovations and viable opportunities. This line of reasoning traces back to the definition of "*general-purpose technology*" (Bresnahan & Trajtenberg, 1995), whereby comparisons can be made with respect to electricity and the internet, underscoring the AI's similar broad applicability and transformative impacts. Indeed, AI technologies are increasingly integrated across diverse industries, impacting everything from healthcare and finance to manufacturing and education. AI's versatility stems from its ability to perform a vast range of tasks, from automating mundane processes to providing advanced analytics and decision-making support (Dwivedi et al., 2021). Moreover, its pervasiveness is not only related to potential widespread adoption but also to innovation itself, as AI acts as a catalyst for further innovation by spurring the emergence of new related or complementary products and services (Van Roy et al., 2020; Obschonka & Audretsch, 2020), thus functioning as a "bridging platform" (Grashof & Kopka, 2023) between previously unconnected technological domains.

This enabling characteristic is even more pronounced if one looks at the role of AI and 4IR technologies in the innovation process itself; they solve the so-called *needle-in-a-hystack problem* by accelerating the transition from inquiry to data-driven research as the knowledge burden increases (Bianchini et al., 2022; Agrawal et al., 2019; Cockburn et al., 2019), whereby research costs can be considered an increasing function of the degree of complexity of the knowledge base upon which a field relies (Fleming, 2001), hampering knowledge recombination practices. For this reason, in addition to being a GPT, AI is also defined as a general-purpose invention in the methods of invention (GP-IMI). This human-AI collaboration can lead to breakthroughs in scientific research in general, whereby AI, by analysing complex datasets and unveiling hidden structures that would otherwise remain undiscovered, might help scientists develop and generate new ideas (Haefner et al., 2021) that might then be commercialised. This line of reasoning also applies to would-be entrepreneurs outside the scientific realm: AI provides powerful tools to explore and exploit new innovative business opportunities, helping them to innovate, optimise operations, and create value in novel ways (Fossen et al., 2024; Chalmers et al., 2021).

Therefore, AI knowledge should be considered extremely useful for innovative startups in general, across industries, for several reasons: *a)* according to their ability to create new AI-related products and services in upstream industries (core AI industries); *b)* due to their capability of spawning complementary innovations in industries characterised by a related technological paradigm, thanks to its cross-sectoral pervasiveness; *c)* as a consequence of their capacity to enable other – either product or process – innovations in downstream industries.

Summing up, high AI-related technological opportunities across the entire economy might be triggering the emergence of new innovative firms that capitalise on them due to their high pervasiveness. In this process, knowledge spillovers might play a crucial role according to: *i)* the high cumulativeness of AI knowledge at the local level, given its localised nature (Audretsch & Feldman, 1996); *ii)* the low appropriability of the benefits stemming from AI inventions, as they are GP-IMI (Cockburn et al., 2019; Schotchmer, 2004); *iii)* the non-rivalry in use of AI technological knowledge (Dosi & Nelson, 2023).

However, so far, discourses regarding the pervasiveness of AI technologies, their enabling nature, the amount of opportunity they entail, as well as their alleged role within innovation processes remain mainly theoretical. For this reason, in this study an explicit attempt is made to test the degree of pervasiveness and the level of opportunities brought about by AI technologies, trying to trace knowledge spillovers at the regional level by correlating the regional AI knowledge stock and the number of new innovative ventures. This perspective offers an ideal technological context where Marshallian, Jacobian and Porter spillovers (see above) and innovative startups should fully exert their driving roles in enhancing innovation and economic growth. In so doing, we provide a practical test of the KSTE+I framework, once singled out AI technologies as the key trigger factor.

In this context, the region where new AI technologies are produced is anticipated to experience an increase in innovative startups, with the magnitude of this effect mediated by knowledge and spillover characteristics. It is important to note that the enabling role of AI technologies is assessed by their potential to foster innovative entry in general (that is new innovative ventures patenting in any technological field, see next sections).

In more detail, by taking a technology-based perspective related to a specific geographical area, we will first test whether the accumulation of AI knowledge (measured in terms of AI patents) is promoting the creation of new innovative ventures at the same regional level and in AI-related industries. In doing so, we relate the regional AI knowledge stock to innovative startups in general (that is new ventures innovating in any technological field) but belonging to high-tech/AI-related industries. This means that we test the enabling role of AI technologies focusing on the complementary innovations arising within those sectors. This perspective can be summarized in our Hypothesis 1:

Hypothesis 1: *The local AI stock of knowledge exerts an enabling role in fostering innovative entry within AI-related local industries (AI technologies as focused enablers).*

Moreover, *if* AI technologies are GPTs and GP-IMI, extensively pervasive, and create generalized opportunities throughout the economy, *then* there should be a positive correlation between the AI knowledge stock and the number of innovative startups at the regional level, regardless of the sector in which new ventures operate. This leads to our second hypothesis:

Hypothesis 2: *The local AI stock of knowledge also exerts an enabling role in fostering innovative entry in non AI-related local industries (AI technologies as generalised enablers).*

3. Data and methodology

Taking into account the discussion and hypotheses put forward in the previous section, our empirical analysis is aimed at testing the level of opportunities (and possible pervasiveness) brought about by AI technologies, firstly, by creating an AI regional knowledge stock capable of capturing the *locus* where these technologies are actually created and, secondly, by explaining regional innovative entrepreneurial engagement as a function of AI opportunities captured by this stock. We focus on European Nuts-2 regions, given the role of geographical proximity in generating knowledge spillovers (broadly discussed in Section 2).

3.1. Knowledge stocks

The first step aims at constructing the regional AI knowledge stock. Building on prior literature (Colombelli & Quatraro, 2018; Colombelli, 2016) and bearing in mind the limitations of patent measures[1], we used patents to proxy AI knowledge. AI patent applications were retrieved using text-mining techniques, therefore looking for the occurrence of a given keyword in either the abstract or title. The list of keywords is borrowed from Damioli et al. (2024): we embrace this list as it comprises the entire ecosystem of technologies revolving around the macro-field of AI (Vannuccini & Prytkova, 2024). Furthermore, in addition to what has previously been proposed by the authors, in Table 1 keywords are grouped according to the macro technological areas to which they pertain, following previous studies showing the complexity of the AI field (Cockburn et al., 2019; van Eck & Waltman, 2007). These partitions are created to maximise the within-similarity among keywords. In particular, "Learning Systems" include technologies capable of learning from raw data and making predictions; "Symbolic Systems" include technologies capable of understanding world phenomena by interpreting symbols; "Autonomous Systems" and "Robotics" are two different groups of technologies, but close in terms of functional definition, as they can be defined as "actuators"[2]; "Virtual and Augmented Reality" are technologies typically used to test the performance of a given technology, such as robots or quadrotors; "Big Data and IoT" represents a group of technologies normally functional to the previous ones, as they are a network of interconnected devices that collect and exchange huge amount of data. This grouping, as well as the inclusion of all the keywords proposed by Damioli et al. (2024), is highly consistent with the definition of an "AI system" provided by the High-Level Expert Group on Artificial Intelligence (2019)[3].

All AI patent applications, applied all around the world from 1990 to 2019[4], were retrieved using Patstat database (2021 version). However, our approach differs from the one used in some previous studies, as we did not simply geolocate patent applications; instead, we used DOCDB patent families[5]. In the Patstat database every patent belongs to a DOCDB family: these contain and group applications that claim the same "active" priority and, therefore, are considered to have the same technological content (Martinez, 2010). Using patent families instead of applications avoids inflating the resulting knowledge stock indicator, as patents within the same family are then counted only once. All patent

[1] In particular: patents can be used strategically, not every invention is patented and their usage is sector-specific. However, as far as our analysis is concerned, patenting is the most reliable indicator capable of providing us with a consistent mapping of AI-related knowledge.
[2] Actuators are technologies that perform the physical movement or control within a system. They receive a signal and respond by producing a specific motion or action, often involving movement or the manipulation of an object.
[3] "*Artificial intelligence (Al) refers to systems that display intelligent behaviour by analysing their environment and taking actions - with some degree of autonomy - to achieve specific goals. Al-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or Al can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications)*" (High-level Expert Group on Artificial Intelligence, 2019).
[4] As we adopt the 2021 version of Patstat database, the year 2020 is affected by severe truncation.
[5] The acronym "DOCDB" stands for "Documentation Database". It is a master database managed by the European Patent Office (EPO) that consolidates and standardizes patent bibliographic data from numerous patent offices worldwide. This database facilitates comprehensive patent searches and analyses by providing a unified format for patent information from different jurisdictions.

families were geolocalised using a methodology similar to the one proposed by de Rassenfosse et al. (2019). For this purpose, inventors' addresses were employed to capture: *a)* the *locus* where the invention was created[6]; *b)* regions boasting the presence of AI specialists and, therefore AI technical knowledge. As we retrieved all AI patents available on Patstat and then aggregated the analysis to the family level, an iterative procedure was followed: first, all the inventors within each family were identified; second, those with a European address were singled out; third, all AI patents families not having at least one European inventor were dropped. Since a large share of addresses are missing in Patstat, this database was integrated using two other sources: PatentsView and Regpat[7]. This procedure resulted in 29,344 patent families successfully geolocalised with priority year between 1990 and 2019; the fractional counting method was used in order to attribute to each region its actual contribution to the invention and, thus, avoid inflation problems in the case of multiple inventors residing in different regions.

Then to build our indicator concerning the AI knowledge stock, the "*permanent inventory method*" (P.I.M.) was employed. In every Nuts-2 region, every year, the total AI knowledge generation is given by:

$$W\_AI_{it} = \sum_{j=1}^{n} w\_AI_{jit} \tag{1}$$

where w_AI_{jit} is the actual contribution of region *i* in patent family *j* having a priority year *t* resulting from the fractional counting procedure. Then, the P.I.M. is recursively computed:

$$K\_AI_{it} = \frac{K\_AI_{it-1}}{(1+\delta)} + W\_AI_{it} \tag{2}$$

where the AI knowledge stock in time *t* and region *i*, is given by the sum of the discounted AI knowledge stock in *t-1* with the total AI technical knowledge produced in *t*. The discount rate was set to δ = 0.15 following Hall et. al. (2005).

As stated in the theoretical setting, taking a technology-based perspective means analysing a specific set of technologies (in our case AI) to grasp their characteristics as well as the entrepreneurial opportunities they create. However, this approach might be somehow *naïve* if one does not take into account the possible more general technological drivers that might affect entrepreneurial opportunities. With the aim of capturing the sole AI-related entrepreneurial opportunities, ICT patents are also retrieved, to control for the overall regional "digital" knowledge endowment. Indeed, as

[6] As shown by Maraut et al. (2008) and de Rassenfosse et al. (2019), the inventor's address usually indicates where the invention was made: it often indicates a laboratory, a research establishment, or the place of residence of the inventor.
[7] The first one covers USPTO patents, the second one WIPO and EPO patents.

shown by previous studies: *a)* ICTs and AI technologies seem to share the same knowledge base (Santarelli et al., 2023); *b)* AI is not a radical break from the past but tends to rely on previous knowledge and technologies, in particular ICTs (Cetrulo & Nuvolari, 2019; Lee & Lee, 2021); *c)* ICTs have been shown to generate entrepreneurial opportunities (von Briel et al., 2018; Song, 2019; Colombelli et al., 2024). Leveraging on these pieces of evidence, ICT patents are retrieved following the same procedure described above but using a list of IPC codes provided by Inaba & Squicciarini (2017): taking the same reference period, 619,757 ICT patent families have been geolocalised[8]. Then the ICT knowledge stock has been computed; both the AI and ICT stocks are normalised for 100,000 inhabitants.

As expected, AI and ICT stocks reveal a high geographical correlation (ρ = 0.71), which is highly consistent with results provided by Xiao and Boschma (2023) showing that local infrastructure and capabilities related to ICTs serve as a "digital base" for the development of AI knowledge in Europe. This piece of evidence, however, makes inadequate to introduce both knowledge indicators into the same empirical model due to multicollinearity problems. Therefore, in addition to the simple AI knowledge stock, we also computed the AI knowledge share as:

$$K\_AI\_share_{it} = \frac{K\_AI_{it}}{K\_AI_{it} + K\_ICT_{it}} \tag{3}$$

While acknowledging that such an indicator constitutes an imperfect strategy to fully control for the impact of ICT knowledge, it will be aimed at testing whether regions with a higher share of AI knowledge, given the total knowledge concerning "digital" technologies, experience a higher amount of innovative entry.

3.2. Other Knowledge-related indicators

As discussed in the relevant literature, AI knowledge is rather complex; therefore, we tried to take into account the qualitative complexity of this stock by creating other variables. First, following the insights provided by Prytkova & Vannuccini (2024) on the systemic nature of AI, an attempt is made to build a variable meant to capture the structure of the AI knowledge stock. In this sense, according to the grouping of keywords proposed in Table 1, we decomposed the AI knowledge stock into its components; each patent family has been assigned to one of the six groups according to the keyword appearing either in the abstract or in the title (see Table 1). Therefore, six different knowledge stocks

[8] As expected, some patent families classified as AI were also found in ICT ones: this evidence further reinforces the correlation between the two fields. For this work, overlapping patent families were dropped from the ICT group, thus giving priority to the AI patent retrieval procedure.

were computed, one for each group, and then the share of each stock over the total AI knowledge. Using these shares, an entropy index was computed by implementing the Shannon entropy measure, given by:

$$Entropy\_AI_{it} = -\sum_{i=1}^{6} s_{ijt} * log_2(s_{ijt}) \quad (4)$$

where s_{ijt} represents the share of technology *j* in year *t* in the AI stock of region i. We allowed this measure to vary over time to account for variation in the AI stock composition. The higher the index, the higher the balance of the AI stock composition. In other words, this index shows whether the AI knowledge stock in a given region is concentrated in a few specific technologies (low value) or is diversified across many technologies (high value). If the argument proposed by Vannuccini & Prytkova (2024) holds, then a positive coefficient in affecting innovative entry is expected; this may also be in line with the Jacobian externality argument (see Section 2) as well as with the "recombinant knowledge approach" (Colombelli & Quatraro, 2018).

Furthermore, as suggested by Cockburn et al. (2019) and Bianchini et al. (2022), among all AI technologies, *neural networks* (NNs) are thought to be the most radical and the ones from which the highest number of technological opportunities should stem from[9]. To investigate if knowledge related to NN technologies, *per se*, is able to spur the creation of innovative firms, we singled out NN families: namely, patents in which the keyword "neural network" appears. Then, we computed the NN knowledge stock as well as the the NN knowledge share, given by:

$$K\_NN\_share_{it} = \frac{K\_NN_{it}}{K\_AI_{it}} \quad (5)$$

where the numerator refers to the NN knowledge stock and the denominator to the overall AI knowledge stock. Given that this measure might be rather limited as it only comprises NN knowledge, we also embraced a more general definition and considered, alternatively, the knowledge related to Learning Systems as well as its share[10].

[9] In particular, NNs belong to a subfield of Machine Learning, namely Deep Learning, whereby these models automatically learn hierarchical representations from raw data by composing multiple layers of transformations, where each layer is composed of multiple artificial neurons (Russell & Norvig, 2016). NNs excel in various tasks, especially in those involving complex patterns, large datasets, and unstructured data types; these tools are highly pervasive and versatile, with their application spanning from quantum physics to medicine. As in Bianchini et al. (2022), their transversal and cross-sectoral applicability is given by their capability to help shoulder the knowledge burden that curtails scientific progress, thus influencing both "search" and "discovery" processes, by: *a)* predicting which pieces of knowledge and information are most relevant in a certain field (i.e., NN-based recommender systems, transformational learning); *b)* discovering hidden associations between existing studies, where the combination of the latter may produce new valuable ideas (i.e., literature-based discovery, machine reading).

[10] As in Table 3, these variables are called K_LEARNING and K_LEARNING_share, respectively.

3.3. Innovative entry

Following the tradition concerning the KSTE+I literature, the dependent variable should be able to capture the spillover effect; in other words, the response variable should proxy the response of would-be innovative entrepreneurs to opportunities stemming from knowledge and technologies created within a given context. Taking a meso-regional approach, some studies have used self-employment rates (Acs et al., 2009), however, this indicator is far from measuring the outcome of knowledge spillovers, since a large portion of self-employment is made by non-innovative or even defensive entrepreneurs (Baumol, 1990).

Another approach would be to measure the number of new entrants in a given region (Bishop, 2012). However, the process of new venture formation, as thoroughly discussed by prior literature, is noisy, with entry and exit rates being highly correlated: indeed, not all new firms are "good" and innovative (Audretsch et al., 1999; Vivarelli, 2004; Santarelli & Vivarelli, 2007; Vivarelli, 2013). Therefore, the alleged positive correlation between a given knowledge base (in our case AI patenting) and entry rates does not confirm, *per se*, the KSTE&I approach[11].

Therefore, to focus on real Schumpeterian startups, other studies focused on new entrants in high-tech sectors (Colombelli & Quatraro, 2018), new firm formation in knowledge-intensive sectors (Bonaccorsi et al., 2013) or the number of innovative start-ups (Colombelli, 2016; Colombelli et al., 2023; Colombelli et al., 2024). Consistently, we adopt a definition capable of proxying the number of new innovative firms in European Nuts-2 regions; unfortunately, at the European level, no predefined measure is available.

Therefore, we followed previous studies that used patenting activities to tag a new firm as innovative (Breschi et al., 2000; Breschi et al., 2014): we define "innovative entry" a firm that applies for a patent within the year of its incorporation in *any* technological field. In so doing, we restrict our focus to the observation units where the "spillover effect" is most likely to be found. To build this series, we relied upon Orbis and Orbis IP data, where the historical patent portfolio of each firm incorporated between 1990 and 2020 was evaluated. In particular, as a first step, all firms born

[11] To illustrate the argument, consider a region characterized by a rich knowledge base and also featuring high entry rates. It could be the case that such a correlation may well be due to a "trial-and-error" strategy (Jovanovic, 1982), resulting in a mere entry of "revolving door" firms (Santarelli & Vivarelli, 2007). Or, to give another interpretation put forward in the field of economic geography, firms may tend to locate in zones because previous locations of similar firms act as a strong "signal" of the opportunities lying in that area (Maggioni, M., 2002); this could be explained by referring to the so-called "herd effect" (Hsieh & Vermeulen, 2014). In either scenario, one can cast several doubts on the alleged role of these new ventures as a Schumpeterian "disruptive force". In a nutshell, "to be born is not enough" (Colombelli et al., 2016) for at least two reasons: first, new ventures are doomed to early failure and, on average, their likelihood of survival after 5 years from incorporation is 50% (a joint analysis of start-ups' growth and survival is provided in Audretsch et al., 1999). Second, the majority of new entrants are inefficient and short-living, whereby most of the survivors rapidly evolve into "zombie firms" (McGowan et al., 2018).

between 1990 and 2020 were retrieved from Orbis and, after a match with Orbis IP database, firms not having at least one patent were removed. As a second step, a patent portfolio for each firm was built, comprising all patent applications the firm applied for; finally, only firms having a patent application in the year of their incorporation were retained. This led to the identification of 27,378 new innovative firms that were then aggregated at the Nuts-2 level: therefore, the "innovative entry" variable represents the count of new innovative firms in European Nuts-2 regions. We remain agnostic as to the technological field in which new firms patent in accordance with our hypotheses stated at the end of Section 2; indeed, our scope is to detect the alleged enabling role of AI technologies in fostering new ventures engaged in any kind of innovative activities.

In order to test our hypotheses, we introduced a sectoral split: the ”innovative entry” variable was divided according to the main NACE code of the new entrant; in particular, new ventures entering into AI-related industries were separated from new entries in NON-AI industries, whereby AI industries are identified by the ten most frequent[12] NACE codes at the family level within the sample of our geolocated AI patents, using applicants as a reference. This split is of crucial importance. One could argue that AI-related industries are those in which these technologies have offered more opportunities, as they represent sectors that produce core and complementary technologies for AI development, as well as related applications (our Hypothesis 1: AI technologies as focused enablers). However, it is also relevant to test whether entrepreneurial opportunities are arising in other industries[13], given the alleged general-purpose nature of AI (our Hypothesis 2: AI technologies as generalised enablers). Therefore, we will argue that a positive correlation between the AI knowledge stock and new innovative entries in AI-related industries would support Hypothesis 1, whereas a positive correlation between the AI knowledge stock and the number of new innovative firms in non-AI-related industries would support Hypothesis 2, thereby confirming the extensive GP nature of AI and its IMI characteristics (Cockburn et al., 2019).

The ten AI-related industries are shown in Table 2: the number of occurrences represents the appearances of a given Nace code within an AI patent family. The emerging picture is rather consistent with the results provided in Santarelli et al. (2023) for the US.

3.4. Control variables

We controlled for several factors that may be correlated with the creation of innovative new firms, whose effects might otherwise bias the coefficients of our key knowledge variables.

[12] Above the mean number of occurrences.
[13] Presumably downstream, adopting industries, therefore capturing vertical spillovers.

First, we controlled for the population density of Nuts-2 regions considered in our sample. This measure controls for agglomeration economies, which might indirectly capture knowledge flows among individuals: a higher density would mean that individuals live in close proximity, which might further affect the exchange of ideas by creating clusters (Cao et al., 2023). This indicator is given by:

$$POP\_DENS_{it} = \frac{POP_{it}}{TOT\_AREA_i} \tag{6}$$

where the numerator refers to the population in region *i* and year *t*, whereas the numerator indicates the total area of the relevant Nuts-2 region in square kilometres[14].

Second, as shown by prior literature, the presence of universities within regions may be a channel that: *i)* attracts talents and feed the ecosystem with highly skilled individuals (Colombelli et al., 2023); *ii)* facilitates knowledge transfer processes from academia to the private sector, as universities are increasingly paying attention to commercialization activities (Carree et al., 2014); *iii)* might spawn academic spin-offs. To this end, we controlled for the number of universities per square kilometer as:

$$UNIV\_DENS_{it} = \frac{UNIV\_COUNT_{it}}{TOT\_AREA_i} \tag{7}$$

where the numerator represents the count of universities in region *i* and year *t*, while the denominator is as in (6).

Third, the entrepreneurship literature has suggested that a driver of new venture creation is the "entrepreneurial and agency culture" of a given region (Parker, 2018a; Carbonara et al., 2018; Audretsch, 2023). As in prior literature, we try to operationalise this construct by introducing in the estimates the self-employment rates:

$$SELF\_EMPL\_RATE_{it} = \frac{SELF\_EMPL_{it}}{TOT\_EMPL_{it}} \tag{8}$$

where the numerator depicts the number of self-employed individuals (both with and without employees) and the denominator the overall employment in region *i* and year *t*.

Fourth, a long tradition in the entrepreneurship and industrial dynamics literature refers to studying the relationship between unemployment and new firm formation (Foti & Vivarelli, 1994; Audretsch & Vivarelli, 1995; Santarelli et al., 2009). Following prior results, the "escape from unemployment" hypothesis has been formulated: high unemployment rates might indicate a lack of alternatives in paid employment, therefore pushing individuals into self-employment. While this channel is unlikely

[14] For constructing all series, we adopted the 2021 Nuts version.

promoting innovative entry, there might be another support to the abovementioned hypothesis: high unemployment might trigger the creation of new firms as it would be cheaper to hire workers, whereby labor is the primary input for newly born firms. We introduce the unemployment rate to control for such mechanisms, given by:

$$UNEMP\_RATE_{it} = \frac{UNEMP_{it}}{TLF_{it}} \tag{9}$$

where the numerator refers to the total number of unemployed individuals and the denominator indicates the civilian total labor force, expressed as the economically active population in region *i* and year *t*.

Fifth, we controlled for the share of High-Tech employment in a given region for different reasons. First of all, it might originate spin-out entrepreneurs (Klepper, 2009; Adams et al., 2016; Qian, 2018; Adams et al., 2019), as knowledge and opportunities may abound in those industries. Furthermore, as AI knowledge has a wide variety of applications - thus hinting at their complexity - a higher share of high-tech employment might also capture a higher regional *absorptive capacity* (Cohen & Levinthal, 1990) of the AI knowledge locally produced. This variable is given by:

$$HT\_EMPL\_SHARE_{it} = \frac{HT\_EMPL_{it}}{TOT\_EMPL_{it}} \tag{10}$$

where the numerator is the employment in High-Tech manufacturing[15] and Knowledge-Intensive services[16], whereas the denominator is as in (8).

Sixth, one concern might be that our knowledge indicators might be highly correlated with the overall inventiveness and knowledge produced within regions (Acs, 2009); therefore, to account for that, we control for the regional R&D intensity, expressed as:

$$R\&D\_INT_{it} = \frac{GERD_{it}}{GVA_{it}} \tag{11}$$

whereby the numerator represents the gross R&D expenditures (considering all sectors) and the denominator the gross value added of region *i*, in year *t*.

Seventh, standard occupational choice models (Knight, 1921; Lucas, 1978; Parker, 2018b) show that the choice between paid employment and self-employment is mainly driven by a comparing the utility stemming from a fixed wage, as determined by the labor market, and the utility stemming from

[15] Nace 21 and 26.
[16] Nace 50, 51, 58 to 63, 64 to 66, 69 to 75, 78, 80, 84 to 93.

expected profits in self-employment. To account for such a mechanism, we introduced the average hourly compensation of employees, given by:

$$COMP\_PH_{it} = \frac{AV.COMPENSATION_{it}}{AV.HOURS\_WORKED_{it}} \tag{12}$$

where the numerator indicates the average compensation of employees, whereas the denominator the average number of hours worked in region *i* and year *t*.

Finally, the entrepreneurship literature has suggested that there might be some relationship between migration and entrepreneurship (Naudé et al., 2017; Parker, 2018a). We control for the net migration rate to account for the intensification of knowledge flows with respect to higher level of migration in a given region, which might result in further spillovers. This index is expressed as:

$$MIG\_RATE_{it} = \frac{IMM_{it} - EMI_{it}}{POP_{it}} \tag{13}$$

where the numerator is given by the total number of immigrants minus the total number of emigrants, while the denominator represents the total population of region *i* in year *t*.

A comprehensive list of variables, as well as the sources used to build them, is provided in Table 3. For data availability issues, the final dataset resulted in an unbalanced panel with 287 Nuts-2 European regions, observed from 2000 to 2020[17]; therefore, the number of new innovative firms (as defined in Section 3.3) drops to 19,655 for this period. Table 4 reports summary statistics; as will be described in the next section, we adopt a lagged model, so the "innovative entry" series is observed until 2020, while all other variables are collected until 2019[18].

4. Econometric Strategy

As far as our econometric strategy is concerned, one must point out the count nature of our dependent variables, being the number of new innovative firms in AI and NON-AI Industries. Moreover, the width of our dataset allows us to include both time and regional fixed effects, thus netting out unobservable factors that might otherwise bias the coefficients of the variables of interest. Therefore, Poisson and Negative binomial models with fixed effects are natural candidates.

[17] Indeed, data on control variables for 1990-1999 are not available. Although such a procedure led to losing the first ten years of our dataset, on the one hand, we managed to collect enough control variables to reduce the bias in the coefficients of our knowledge indicators and, on the other hand, we can still leverage on a twenty-years period to test our hypotheses (indeed, the time span central to the diffusion of AI technologies).

[18] This explains the difference in observations in Table 4 for the "innovative entry" series and the other variables.

Econometric scholars have argued, however, that: *i)* the conditional Negative Binomial Fixed-Effect (NBFE) estimator, as proposed by Hausman, Hall, and Griliches (1984), has peculiar properties which make it unreliable as it does not control for all stable covariates. In this respect, unconditional NBFE models have been shown to perform better in capturing fixed effects by estimating them (Allison & Waterman, 2002); *ii)* the Poisson Fixed-Effect (PFE) estimator is still robust to unconditional overdispersion once fixed effects are controlled for (Correia et al., 2019; Guimaraes, 2008; Wooldridge, 1999). Taking stock of this debate, we present results for both unconditional NBFE and PFE, on the one hand, to be certain that our results are not determined by either estimator and, on the other hand, to test for the robustness and consistency of our findings.

Taking into account what discussed in Section 3, we propose two specifications. As regards the first one, three main explanatory variables are considered: i) the AI knowledge stock; b) the AI knowledge share; c) the entropy index measuring the diversity of the AI knowledge stock. Therefore, we estimate the following model:

$$E[ENTRY_{it} \mid \theta] = \exp\left(\beta_1 K_{AI\,it-1} + \beta_2 K_{AI_{share}\,it-1} + \beta_3 Entropy_{AI\,it-1} + \sum_{i=1}^{8} \beta X_{it-1} + \tau_t + \varphi_i + \varepsilon_{it}\right) \tag{14}$$

Furthermore, with the aim of better understanding entrepreneurial opportunities generated by NNs and learning systems (see Section 3.2), we propose a second specification where four main explanatory variables are considered: i) the NN knowledge stock; ii) the NN knowledge share; iii) the Learning Systems knowledge stock; iv) the Learning System knowledge share. This resulted in the following model:

$$E[ENTRY_{it} \mid \theta] = \exp\left(\beta_1 K_{NN\,it-1} + \beta_2 K_{NN_{share}\,it-1} + \beta_3 K_{Learning\,it-1} + \beta_4 K_{Learning_{share}\,it-1} + \sum_{i=1}^{8} \beta X_{it-1} + \tau_t + \varphi_i + \varepsilon_{it}\right) \tag{15}$$

Both models are estimated for AI-related and non-AI-related industries to check for differences in the coefficients and test our key hypotheses (see Section 2); note that all regressors are lagged by one year[19]. Furthermore, each model includes the controls introduced above, time and Nuts-2 fixed effects.

[19] The lag allows spillovers to operate and avoids possible endogeneity. However, our stock/flow specification (the cumulated stock of AI knowledge affecting the innovative entry flow) is intrinsically robust to endogeneity issues.

5. Regression results

Starting from the first specification, Table 5 shows the results of the estimates for the Poisson model. Looking at AI-related industries, the AI knowledge stock is positive and significant ($p<0.01$ – column 1; $p<0.001$ – column 2), confirming our idea that AI technologies have created significant opportunities within industries characterised by knowledge bases capable of exploiting them. Focusing our attention on the AI knowledge share, we still confirm the result provided above even after controlling for the overall digital knowledge: AI technologies are delivering opportunities in AI sectors besides ICT-related knowledge as the coefficient is positive and significant ($p<0.01$ – column 3; $p<0.01$ – column 4). However, since the AI knowledge stock and the AI knowledge share have two different scales, the magnitude of the effects cannot be compared; despite that, there is a confirmation of Hypothesis 1 stated in Section 2.2 for AI-related industries. As regards the entropy measure, results show a positive and significant coefficient ($p<0.001$ – column 2; $p<0.001$ – column 3); this is in line with the argument proposed by Vannuccini & Prytkova (2024), whereby the higher the variety, the more the opportunities and therefore the number of new innovative entrants capitalising on them in a recombinant fashion (Weitzman, 1998; Colombelli & Quatraro, 2018).

However, if one focuses on non-AI-related industries a very different picture emerges: while all being positive, not even a single key regressor is significant at the 5%. Therefore, Hypothesis 2 stated in Section 2.2 concerning non-AI-related industries is rejected.

On the whole, the enabling nature of AI technologies is supported but limited to the high-tech/AI-related industries (AI as focused enablers)

Table 6 reports the coefficients of the first specification using the unconditional NBFE, and results for AI-related industries are statistically equivalent, with the main difference being the level of significance of the AI knowledge stock in column 1 ($p<0.05$) and the AI share in column 4 ($p<0.05$); however, coefficients are all significant at least at the 5% level of confidence. Regarding non-AI Industries, none of the indicators are significant, confirming the evidence in Table 5.

As regards the second specification, whereby we focus our attention on a specific technology, namely NNs, results are shown in Tables 7 and 8. Focusing on Table 7 (PFE model) and looking at AI-related industries, the NN knowledge stock is positively and significantly correlated with the creation of new innovative firms ($p<0.001$); however, when using the NN knowledge share as the main explanatory variable, this indicator turns out insignificant. A similar pattern emerges when using the Learning System knowledge indicator: the stock is positive and significant ($p<0.001$), although halved in terms of magnitude, whereas the share is not significant. This piece of evidence further confirms the results provided in Tables 5 and 6 concerning the entropy measure: more entrepreneurial and technological opportunities are created when regional knowledge stocks are variegated in terms of technological knowledge. Looking at non-AI-related industries, results confirm the lack of a generalised spillover: even focusing on a specific, general-purpose technology, it seems that NN-related knowledge is not so useful outside AI-related industries as it does not create exploitable opportunities. Considering the results shown in Table 8 obtained estimating a NBFE model, coefficients are almost identical both in terms of significance and magnitude.

Briefly looking at the control variables, it could be argued that: first, agglomeration economies are only relevant for firms entering non-AI-related industries. Second, the unemployment rate is never significant, confirming that the firms we are dealing with can be defined as Schumpeterian (Santarelli & Vivarelli, 2007; Vivarelli, 2013). Third, the number of universities fails to be significant, which could hint that there is a huge heterogeneity within academia in terms of quality across European regions (Bonaccorsi et al., 2014; Carree et al., 2014). Fourth, the self-employment rate is generally non-significant and shows an unexpected sign, casting some doubts about the goodness of such an indicator to proxy the "entrepreneurial culture" of a region (Poschke, 2019). Fifth, High-tech employment seems to be of some importance for all new innovative entrants (regardless of the industrial classification), which supports both the spin-off hypothesis and the knowledge flows argument. Sixth – somehow surprisingly – R&D intensity is not significant; this outcome might be due to the presence of R&D laboratories located in large corporations massively leveraging on different appropriability tools (Kotsios et al., 2015). Seventh, as regards the migration rate, it is positively and significantly correlated only with new entrants in AI industries: perhaps, in non-AI-related industries knowledge flows stemming from agglomeration economies are more important, whereas in AI industries a more crucial role is played by cross-border knowledge flows. Finally, considering the average hourly compensation, the coefficients have the expected sign – negative – but are only significant for non-AI-related industries: this could mean that opportunities in AI industries may be so high that would-be entrepreneurs do not consider higher wages as particularly crucial.

6. Conclusions

In this paper we integrate the insights of the Knowledge Spillover Theory of Entrepreneurship and Innovation with Schumpeter's idea that innovative entrepreneurs creatively apply available local knowledge, possibly mediated by Marshallian, Jacobian and Porter spillovers. However, while previous literature (discussed in Section 2) has widely proved that technological revolutions are the ideal terrain where innovative entry can fully play its creative/destructive role, the KSTE+I approach - while being illuminating in highlighting the channels and hindrances characterising the geographically localised spillover effects and the role of innovative startups (see Section 2.1) - remains very general as far as the particular nature of technology is concerned. On the other hand, the current debate about the advent of AI technologies, their alleged pervasiveness, their enabling nature and the amount of opportunities they entail remain mainly theoretical (see Section 2.2).

To fill these gaps in the extant literature, in this study we assess the degree of pervasiveness and the level of opportunities brought about by AI technologies by testing the possible correlation between the regional AI knowledge stock and the number of new innovative ventures (that is startups patenting in any technological field in the year of their foundation). In so doing, we provide an empirical test of the KSTE+I framework, once isolated AI technologies as the key trigger factor.

More in detail, focusing on 287 Nuts-2 European regions, we built the AI knowledge stocks using patent data; we geolocalised 19,655 new innovative firms (over the time span 2000-2020) and we tested whether the local AI stock of knowledge exerts an enabling role in fostering innovative entry within AI-related local industries (AI technologies as focused enablers) and within non AI-related local industries (AI technologies as generalised enablers).

Results from Negative Binomial fixed-effect and Poisson fixed-effect regressions (controlled for a variety of concurrent drivers of entrepreneurship) reveal that the AI knowledge stock does promote the spread of innovative startups, so supporting both the KSTE+I approach and the enabling role of AI technologies; however, this relationship is confirmed for the sole high-tech/AI-related industries and not for the non-AI related sectors. Therefore, as far as our analysis is concerned, AI technologies emerge as *focused* (and not generalised) enablers.

In terms of possible policy implications, these outcomes call for regional interventions supporting the generation and diffusion of AI technologies, being aware that increasing the local AI knowledge stock can generate spillovers able to foster innovative startups. Furthermore, such interventions should be directed towards creating a balanced knowledge stock, without neglecting the systemic nature of AI: overall, AI technologies may be seen as an infrastructural system, whose components synergically create a complex network which is more than the mere sum of its parts. However, policymakers should also be conscious that - for the time being - this enabling impact of AI technologies is limited to the high-tech/AI-related industries.

Table 1. AI keywords

Learning Systems	Virtual and Augmented Reality	Autonomous Systems	Big data and IoT	Symbolic systems	Robotics
Artificial intelligen*	Artificial realt*	Autonomous car	Big data	Computer vision	Machine to machine
Bayesian model	Augmented realit*	Automatic classification	Data mining	Face recognition	Robot
Computational neuroscience	Holographic display	Automatic control	Data science	Facial recognition	
Decision tree	Mixed realit*	Autonomous vehicle	Internet of things	Gesture recognition	
Deep learn*	Virtual realit*	Self driv*		Natural language processing	
Evolutionary computation	Smart glasses	Unmanned aerial vehicle		Object detection	
Knowledge representation		Unmanned aircraft system		Speech recognition	
Machine intelligen*		Unmanned vehicle		Voice recognition	
Machine learn*				Sentiment Analysis	
Neural net*					
Predictive model					
Probabilistic model					
Random forest					
Reinforcement learn*					
Statistical learn*					
Supervised learn*					
Transfer learn*					
Unsupervised learn*					

Note: The asterisk indicates the truncation of the term to its root used during the text analysis.

Table 2. AI industries

NACE 2-digit	Description	Occurrences
26	Manufacture of computer, electronic and optical products	4327
28	Manufacture of machinery and equipment n.e.c.	3687
72	Scientific research and development	2760
62	Computer programming, consultancy and related activities	2731
29	Manufacture of motor vehicles, trailers and semi-trailers	2681
27	Manufacture of electrical equipment	2175
85	Education	1018
71	Architectural and engineering activities; technical testing and analysis	992
46	Wholesale trade, except of motor vehicles and motorcycles	949
64	Financial service activities, except insurance and pension funding	913

Note: The table displays the ten most frequent 2-digit NACE codes among applicants within the sample of geolocalized AI patent families. The occurrences represent the raw count of AI patent families associated with each NACE code, using the applicants as the reference. This classification mitigates inflation due to family size and is less influenced by strategic patenting activities, thereby providing a clearer depiction of European industries producing AI technologies.

Table 3. Variables

Name	Description	Source
Entry_AI	Count of new innovative firms within AI industries	Author's elaboration based on Orbis and Orbis IP
Entry_NON_AI	Count of new innovative firms within NON-AI industries	Author's elaboration based on Orbis and Orbis IP
K_AI	AI knowledge stock per 100,000 inhabitants	Author's elaboration based on Patstat, PatentsView and Regpat data
K_AI_share	AI knowledge as a share of total knowledge	Author's elaboration based on Patstat, PatentsView and Regpat data
K_ICT	ICT knowledge stock per 100,000 inhabitants	Author's elaboration based on Patstat, PatentsView and Regpat data
Entropy_AI	Entropy measure of the AI knowledge stock	Author's elaboration based on Patstat, PatentsView and Regpat data
K_NN	NN knowledge stock per 100,000 inhabitants	Author's elaboration based on Patstat, PatentsView and Regpat data
K_NN_share	NN knowledge as a share of AI knowledge	Author's elaboration based on Patstat, PatentsView and Regpat data
K_LEARNING	Learning Systems knowledge stock per 100,000 inhabitants	Author's elaboration based on Patstat, PatentsView and Regpat data
K_LEARNING_share	Learning Systems knowledge as a share of AI knowledge	Author's elaboration based on Patstat, PatentsView and Regpat data
POP_DENS	Population density	Ardeco and Eurostat
UNEMP_RATE	Unemployment rate	Ardeco and Eurostat
UNIV_DENS	Number of universities per square kilometer	ETER database
SELF_EMPL_RATE	Share of self-employed individuals	Ardeco and Eurostat
HT_EMPL_SHARE	Share of high-tech employment	Ardeco and Eurostat
R&D_INT	Ratio between R&D expenditures and Gross Value Added	Ardeco and Eurostat
MIG_RATE	Net migration over total population on 1st January	Ardeco and Eurostat
COMP_PH	Average hourly compensation of employees	Ardeco and Eurostat

Table 4. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry_AI	5633	1.765	2.626	0	25
Entry_NON_AI	5633	1.724	2.394	0	28
K_AI	5346	1.077	2.081	0	57.735
K_AI_share	5346	.049	.05	0	.82
K_ICT	5346	27.831	45.78	0	348.589
Entropy_AI	5346	1.248	.762	0	2.55
K_NN	5346	.096	.447	0	20.294
K_NN_share	5346	.086	.15	0	1
K_LEARNING	5346	.175	.792	0	34.649
K_LEARNING_share	5346	.145	.195	0	1
POP_DENS	5346	430.811	1109.949	2.718	10920.49
UNEMP_RATE	5346	.077	.046	.011	.4
UNIV_DENS	5346	.005	.027	0	.404
SELF_EMPL_RATE	5346	.148	.064	.036	.497
HT_EMPL_SHARE	5346	.039	.019	.005	.128
R&D_INT	5346	.017	.013	.001	.136
MIG_RATE	5346	.003	.007	-.092	.079
COMP_PH	5346	22.919	11.12	2.2	60.3

Table 5. Fixed-effects Poisson regressions. AI specification

	AI Industries				NON-AI Industries			
	(1) P-FE	(2) P-FE	(3) P-FE	(4) P-FE	(5) P-FE	(6) P-FE	(7) P-FE	(8) P-FE
K_AI	0.0104**	0.0144***			0.00997	0.0112		
	(0.00341)	(0.00339)			(0.00620)	(0.00620)		
Entropy_AI		0.182***		0.149***		0.0521		0.0289
		(0.0429)		(0.0422)		(0.0423)		(0.0418)
K_AI_share			1.881**	1.789**			0.470	0.438
			(0.591)	(0.598)			(0.643)	(0.649)
POP_DENS	0.000151	0.000190	0.000104	0.000127	0.000472***	0.000484***	0.000431***	0.000435***
	(0.000112)	(0.000115)	(0.000115)	(0.000120)	(0.000124)	(0.000124)	(0.000126)	(0.000127)
UNEMP_RATE	0.198	0.101	0.302	0.248	-0.281	-0.307	-0.217	-0.227
	(0.525)	(0.528)	(0.525)	(0.530)	(0.523)	(0.523)	(0.532)	(0.533)
UNIV_DENS	1.937	2.141	3.503	4.278	-0.305	-0.296	1.712	1.865
	(2.143)	(2.197)	(2.180)	(2.311)	(2.782)	(2.789)	(2.732)	(2.729)
SELF_EMPL_R	-1.755*	-1.603	-1.573	-1.379	-1.224	-1.167	-1.043	-1.000
	(0.856)	(0.857)	(0.862)	(0.869)	(0.877)	(0.878)	(0.907)	(0.907)
HT_EMPL	6.783***	5.495**	6.577***	5.631**	3.280	2.939	3.407*	3.242
	(1.797)	(1.827)	(1.797)	(1.833)	(1.727)	(1.762)	(1.717)	(1.735)
R&D_INT	-4.025	-3.554	-3.790	-3.337	-3.230	-3.089	-2.994	-2.901
	(3.220)	(3.181)	(3.210)	(3.178)	(3.165)	(3.161)	(3.157)	(3.160)
MIG_RATE	2.026*	2.181*	2.470*	2.814*	1.710	1.778	2.206	2.284
	(1.004)	(1.028)	(1.093)	(1.187)	(1.184)	(1.177)	(1.473)	(1.475)
COMP_PH	-0.0116	-0.0117	-0.00835	-0.00758	-0.0207*	-0.0207*	-0.0187*	-0.0186*
	(0.00876)	(0.00876)	(0.00891)	(0.00897)	(0.00882)	(0.00882)	(0.00882)	(0.00881)
CONSTANT	0.868**	0.618*	0.707*	0.469	0.871**	0.796**	0.781**	0.735*
	(0.287)	(0.295)	(0.290)	(0.300)	(0.285)	(0.289)	(0.284)	(0.288)
Observations	5,050	5,050	5,050	5,050	5,116	5,116	5,116	5,116
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Nuts-2 FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses. P-values are represented by: *** p<0.001, ** p<0.01, * p<0.05. All regressors are lagged by one year.

Table 6. Fixed-effects Negative Binomial regressions. AI specification

	AI Industries				NON-AI Industries			
	(1) NB-FE	(2) NB-FE	(3) NB-FE	(4) NB-FE	(5) NB-FE	(6) NB-FE	(7) NB-FE	(8) NB-FE
K_AI	0.00932*	0.0136***			0.00933	0.0106		
	(0.00380)	(0.00374)			(0.00612)	(0.00613)		
Entropy_AI		0.183***		0.154**		0.0525		0.0331
		(0.0427)		(0.0537)		(0.0423)		(0.0417)
K_AI_share			1.796**	1.666*			0.423	0.381
			(0.591)	(0.785)			(0.623)	(0.628)
POP_DENS	0.000168	0.000208	0.000126	0.000150	0.000481***	0.000495***	0.000443***	0.000448***
	(0.000114)	(0.000116)	(0.000116)	(0.000119)	(0.000124)	(0.000125)	(0.000125)	(0.000126)
UNEMP_RATE	0.194	0.101	0.280	0.227	-0.313	-0.338	-0.256	-0.267
	(0.521)	(0.525)	(0.521)	(0.584)	(0.521)	(0.521)	(0.528)	(0.528)
UNIV_DENS	1.392	1.602	2.645	3.430	-0.102	-0.101	1.657	1.822
	(2.144)	(2.189)	(2.165)	(3.103)	(2.790)	(2.797)	(2.663)	(2.663)
SELF_EMPL_R	-1.677*	-1.508	-1.524	-1.313	-1.339	-1.276	-1.175	-1.123
	(0.855)	(0.857)	(0.860)	(1.038)	(0.878)	(0.880)	(0.896)	(0.897)
HT_EMPL	7.289***	5.868**	7.078***	6.019**	3.494*	3.129	3.625*	3.424*
	(1.788)	(1.817)	(1.785)	(2.159)	(1.732)	(1.765)	(1.722)	(1.743)
R&D_INT	-3.891	-3.347	-3.685	-3.150	-3.079	-2.931	-2.876	-2.766
	(3.208)	(3.168)	(3.197)	(3.144)	(3.154)	(3.150)	(3.151)	(3.153)
MIG_RATE	2.091*	2.260*	2.438*	2.806**	1.683	1.757	2.163	2.259
	(1.033)	(1.048)	(1.107)	(0.950)	(1.195)	(1.191)	(1.443)	(1.453)
COMP_PH	-0.0109	-0.0110	-0.00788	-0.00708	-0.0194*	-0.0195*	-0.0174*	-0.0172
	(0.00879)	(0.00878)	(0.00888)	(0.0101)	(0.00885)	(0.00885)	(0.00883)	(0.00883)
CONSTANT	-18.35	-16.94***	-16.72***	-16.92***	-1.781**	-1.788**	-1.867**	-1.877**
	(19.06)	(2.295)	(1.272)	(1.038)	(0.576)	(0.576)	(0.576)	(0.576)
Ln_alpha	-3.667***	-3.718***	-3.643***	-3.656***	-3.862***	-3.864***	-3.785***	-3.777***
	(0.307)	(0.321)	(0.296)	(0.352)	(0.405)	(0.407)	(0.382)	(0.380)
Observations	5,336	5,336	5,336	5,336	5,336	5,336	5,336	5,336
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Nuts-2 FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses. P-values are represented by: *** p<0.001, ** p<0.01, * p<0.05. All regressors are lagged by one year.

Table 7. Fixed-effects Poisson regression. Neural networks specification

	AI Industries				NON-AI Industries			
	(1) P-FE	(2) P-FE	(3) P-FE	(4) P-FE	(5) P-FE	(6) P-FE	(7) P-FE	(8) P-FE
K_NN	0.0326***				0.0285			
	(0.00759)				(0.0169)			
K_NN_share		-0.0104				0.110		
		(0.146)				(0.139)		
K_Learning			0.0186***				0.0158	
			(0.00474)				(0.0103)	
K_Learning_share				-0.0717				0.110
				(0.121)				(0.118)
POP_DENS	0.000148	0.000116	0.000146	0.000126	0.000467***	0.000430***	0.000464***	0.000419***
	(0.000114)	(0.000118)	(0.000114)	(0.000120)	(0.000126)	(0.000126)	(0.000124)	(0.000127)
UNEMP_RATE	0.146	0.279	0.153	0.288	-0.318	-0.236	-0.309	-0.236
	(0.526)	(0.530)	(0.526)	(0.530)	(0.524)	(0.533)	(0.524)	(0.534)
UNIV_DENS	1.705	3.907	1.794	3.889	-0.285	1.749	-0.142	1.819
	(2.141)	(2.291)	(2.146)	(2.300)	(2.750)	(2.739)	(2.736)	(2.735)
SELF_EMPL_R	-1.833*	-1.538	-1.829*	-1.529	-1.261	-1.008	-1.249	-1.018
	(0.858)	(0.866)	(0.858)	(0.865)	(0.878)	(0.908)	(0.877)	(0.909)
HT_EMPL	6.709***	7.045***	6.713***	7.132***	3.240	3.429*	3.245	3.355
	(1.800)	(1.813)	(1.800)	(1.818)	(1.731)	(1.712)	(1.732)	(1.721)
R&D_INT	-4.116	-3.778	-4.130	-3.655	-3.239	-3.177	-3.238	-3.210
	(3.223)	(3.207)	(3.223)	(3.203)	(3.171)	(3.161)	(3.171)	(3.160)
MIG_RATE	1.810	2.681*	1.858	2.722*	1.603	2.207	1.660	2.171
	(1.003)	(1.202)	(1.003)	(1.212)	(1.184)	(1.497)	(1.187)	(1.501)
COMP_PH	-0.0105	-0.00888	-0.0109	-0.00856	-0.0198*	-0.0188*	-0.0200*	-0.0192*
	(0.00876)	(0.00894)	(0.00876)	(0.00895)	(0.00879)	(0.00876)	(0.00880)	(0.00874)
CONSTANT	0.868**	0.757**	0.880**	0.743*	0.866**	0.787**	0.873**	0.807**
	(0.286)	(0.291)	(0.287)	(0.291)	(0.284)	(0.280)	(0.285)	(0.279)
Observations	5,050	5,050	5,050	5,050	5,116	5,116	5,116	5,116
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Nuts-2 FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses. P-values are represented by: *** p<0.001, ** p<0.01, * p<0.05. All regressors are lagged by one year.

Table 8. Fixed-effects Negative Binomial regression. Neural networks specification

	AI Industries				NON-AI Industries			
	(1) NB-FE	(2) NB-FE	(3) NB-FE	(4) NB-FE	(5) NB-FE	(6) NB-FE	(7) NB-FE	(8) NB-FE
K_NN	0.0326***				0.0283			
	(0.00813)				(0.0168)			
K_NN_share		0.00364				0.0997		
		(0.176)				(0.138)		
K_Learning			0.0182***				0.0152	
			(0.00514)				(0.0102)	
K_Learning_share				-0.0627				0.0979
				(0.141)				(0.119)
POP_DENS	0.000170	0.000138	0.000167	0.000147	0.000480***	0.000442***	0.000475***	0.000432***
	(0.000116)	(0.000112)	(0.000115)	(0.000118)	(0.000126)	(0.000125)	(0.000124)	(0.000125)
UNEMP_RATE	0.141	0.257	0.150	0.266	-0.350	-0.272	-0.339	-0.272
	(0.522)	(0.618)	(0.522)	(0.618)	(0.521)	(0.529)	(0.522)	(0.529)
UNIV_DENS	0.999	2.952	1.127	2.948	-0.195	1.687	-0.0154	1.749
	(2.131)	(3.071)	(2.136)	(3.063)	(2.771)	(2.661)	(2.752)	(2.658)
SELF_EMPL_R	-1.765*	-1.499	-1.756*	-1.496	-1.384	-1.142	-1.367	-1.152
	(0.858)	(1.042)	(0.857)	(1.042)	(0.880)	(0.896)	(0.879)	(0.898)
HT_EMPL	7.180***	7.548***	7.193***	7.630***	3.435*	3.649*	3.449*	3.584*
	(1.788)	(2.265)	(1.788)	(2.265)	(1.735)	(1.719)	(1.736)	(1.728)
R&D_INT	-3.986	-3.699	-3.995	-3.570	-3.093	-3.045	-3.092	-3.077
	(3.210)	(3.154)	(3.211)	(3.151)	(3.159)	(3.156)	(3.158)	(3.156)
MIG_RATE	1.843	2.631**	1.903	2.673**	1.550	2.164	1.622	2.134
	(1.028)	(1.011)	(1.029)	(1.013)	(1.192)	(1.461)	(1.199)	(1.466)
COMP_PH	-0.0101	-0.00844	-0.0104	-0.00815	-0.0186*	-0.0175*	-0.0189*	-0.0178*
	(0.00877)	(0.0100)	(0.00877)	(0.00995)	(0.00882)	(0.00878)	(0.00883)	(0.00877)
CONSTANT	-16.89***	-17.98***	-17.24***	-18.22***	-1.795**	-1.859**	-1.791**	-1.845**
	(3.366)	(1.039)	(3.724)	(1.038)	(0.576)	(0.576)	(0.576)	(0.576)
Ln_alpha	-3.661***	-3.590***	-3.662***	-3.594***	-3.853***	-3.787***	-3.851***	-3.793***
	(0.304)	(0.340)	(0.305)	(0.339)	(0.400)	(0.386)	(0.399)	(0.388)
Observations	5,336	5,336	5,336	5,336	5,336	5,336	5,336	5,336
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Nuts-2 FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses. P-values are represented by: *** p<0.001, ** p<0.01, * p<0.05. All regressors are lagged by one year.

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