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ORIGINAL PAPER

The emergence of artificial intelligence in European regions: the role of a local ICT base

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Abstract
The purpose of this study is to investigate how a regional knowledge base of information and communication technologies (ICTs) influences the emergence of artificial intelligence (AI) technologies in European regions. Relying on patent data and studying the knowledge production of AI technologies in 233 European regions in the period from 1994 to 2017, our study reveals three results. First, ICTs are a major knowledge source of AI technologies, and their importance has been increasing over time. Second, a regional knowledge base of ICTs is highly relevant for regions to engage in AI inventing. Third, the effects of a regional knowledge base of ICTs are stronger for regions that have recently caught up regarding AI inventing. Our findings suggest that ICTs play a critically enabling role for regions to diversify into AI technologies, especially for regions' catching up in terms of AI inventing.

JEL Classification O33 · R11 · O31

1 Introduction

Artificial intelligence (AI) has been drawing increasing attention in both academic and policy circles, due to its disruptive nature and enormous growth potential (Agrawal et al. 2019; Buarque et al. 2020; European Commission 2018). AI can be relevant to any intellectual task performed by machines (Russell and Norvig 2010).

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In this sense, AI is expected to have a pervasive role in the economy. Scholars have emphasized the potential of AI as the next general purpose technology (GPT),[1] and how AI could revolutionize the economy by penetrating and transforming a wide range of sectors (Agrawal et al. 2019; Brynjolfsson et al. 2019; Cockburn et al. 2019; Trajtenberg 2019). From a regional perspective, the diffusion of AI entails new opportunities for a region to expand its technological portfolio and create new growth paths, which matters for the region's structural change and long-term sustainable development.

What drives the emergence of new technologies or growth paths in a region has been one of the core topics in the field of evolutionary economic geography (Boschma and Frenken 2006). This strand of literature approaches regional diversification as a process of regional branching: New technologies or activities are more likely to emerge in a region when they are related to the preexisting local capabilities (Frenken and Boschma 2007; Boschma 2017). Technological relatedness is argued to capture cognitive proximity which, along with other dimensions such as geographical or institutional proximity, could facilitate knowledge diffusion within regions and thus explain why related technological activities are more likely to emerge (Rigby 2015; Boschma 2017). This group of research has often focused on the average effects of technological relatedness. However, the importance of technological relatedness may differ by types of preexisting technologies. Technological evolution is argued to be driven by a few GPTs (Bresnahan and Trajtenberg 1995). Following this logic, regions differ substantially in terms of technological and industrial structures as a consequence of previous GPTs, which sets the limitations to the emergence of future technologies.

Surprisingly, little attention has been paid to how regional branching is influenced by GPTs. GPTs have been emphasized as a key tool for smart specialization policy, as the diffusion of GPTs is believed to create new opportunities through the co-invention of applications (Foray et al. 2009; Montresor and Quatraro 2017). Information and communication technologies (ICTs) are widely considered the currently predominant GPTs, displaying an ability to spawn future innovations and having applications across a wide range of sectors (see, e.g., Basu and Fernald 2007; Cardona et al. 2013; Jovanovic and Rousseau 2005). However, our knowledge of how the technological relatedness of ICTs influences regional technological evolution is limited.

To fill the gap, this study aims to investigate how a regional knowledge base of ICTs influences the emergence of AI technologies in European regions. We argue that ICTs, as the currently predominant GPT, should play a critical role in breeding the next generation of digital technologies in general and AI technologies in particular. First, ICTs provide a knowledge base and building blocks that equip regions with digital capabilities and infrastructures to underpin the local capabilities of capturing AI opportunities. Second, the diffusion of ICTs unlocks new technological

[1] Bresnahan and Trajtenberg (1995) coined the term "general purpose technologies" to highlight a few radical technologies characterized by three main features: pervasive use in a wide range of sectors, technological dynamism, and the ability to spawn future innovations.

opportunities for AI and thus increases recombination possibilities for regional technological diversification.

Recent empirical studies have directed attention to regional diversification processes of newly emerging technologies, such as fuel cell technologies, nanotechnologies, biotechnologies, and Industry 4.0 technologies (including AI) (Balland and Boschma 2021; Colombelli et al. 2014; Feldman et al. 2015; Heimeriks and Boschma 2014; Laffi and Boschma 2021; Montresor and Quatraro 2017; Tanner 2016). Few studies, however, have examined the regional evolution of AI. One of the main reasons is attributed to the lack of appropriate data (Buarque et al. 2020). Over the last couple of years, EPO (2017) and WIPO (2020) have separately released methods to identify AI patents based on key phrase or patent classification code searching. Among the limited studies on regional development related to AI, Buarque et al.'s study (2020) focuses on the geographical mapping of AI technologies in European regions and explores the role of AI in regional knowledge networks. They find that AI successful regions are more likely to be the regions where AI technologies are most embedded in their knowledge space. A study by Balland and Boschma (2021) focuses on the regional knowledge production of Industry 4.0 technologies (including AI) in general. They find that a new Industry 4.0 technology is more likely to emerge in a European region if the existing technologies in the region are highly related to Industry 4.0 technologies. A very recent study by Laffi and Boschma (2021) provides more direct evidence showing that the probability of the emergence of Industry 4.0 technologies is higher for regions that specialize in Industry 3.0 technologies. These studies concentrate either on the current position of AI technologies in the knowledge space or on the relationship between Industry 3.0 and Industry 4.0 technologies in general.

The role of GPTs in technological diversification has been neglected in the extant literature. One exception is the study by Montresor and Quatraro (2017). They examine the effects of GPTs by focusing on a group of new generation key enabling technologies, such as industrial biotechnology and nanotechnology. However, there has been no direct evidence exploring how GPTs influence the emergence of AI at the regional level. Particularly, to our best knowledge, to date there have been no studies that have explicitly explored which technologies serve as the main knowledge sources of AI technologies.

To explore how a regional knowledge base of ICTs influences the emergence of AI technologies, we built a dataset for the period from 1994 to 2017 based on the patent data from the OECD REGPAT database. We use the PATENTSCOPE Artificial Intelligence Index developed by the World Intellectual Property Organization (WIPO 2019, 2020) to identify AI patent applications. Following the definitions of WIPO and OECD, our study focuses on AI technologies within the scope of artificial narrow intelligence (ANI), where AI systems are defined as machine-based learning systems designed to accomplish a specific problem-solving or decision-making task with varying levels of autonomy (OECD 2019; WIPO 2019). To analyze the knowledge source of AI technologies, we conduct a citation analysis to identify the technological fields of the patents that were cited by AI patent applications. We find that instruments and ICTs are two major knowledge sources cited by AI patent applications. Among others, the importance of ICTs, particularly advanced digital technologies, has become increasingly significant over time. In the period from 2012 to 2017, ICTs have surpassed instruments and become the largest knowledge source cited by AI patent applications. In addition, we calculate the average technological relatedness of ICTs to a region's existing knowledge base and model its effects on regional knowledge production of AI. Based on a fixed-effects negative binomial model, we find that a high regional level of technological relatedness of ICTs increases AI inventing. The effects of technological relatedness of ICTs are stronger for regions which have recently caught up regarding AI inventing.

The rest of the paper proceeds as follows. Section 2 briefly reviews the relevant literature and discusses the theoretical background. Section 3 describes the data and methodology. Section 4 presents the analyses and the findings, and the final section concludes and discusses the paper.

2 Theoretical background

2.1 Technological relatedness, recombination, and regional diversification

Regional diversification concerns the emergence of new economic activities and new growth paths (Neffke et al. 2011; Isaksen 2015; Tanner 2016), which matters for structural change and long-term sustainable development of a region (Content and Frenken 2016; McCann 2013). The extant literature has emphasized two critical mechanisms of regional diversification. The first mechanism is the recombination process. In his seminal work, Schumpeter (1934) proposes "the carrying out of new combinations," which is perceived as the critical action behind knowledge creation and innovation (Weitzman 1998) and is highlighted as a key mechanism behind regional diversification, enabling recombining as well as modifying existing capabilities. The other mechanism is knowledge diffusion. Technological relatedness captures the cognitive dimension of proximity which, along with other dimensions such as geographical or institutional proximity, is believed to facilitate knowledge transmission and spillovers through promoting interactive learning (Boschma 2017). Learning allows agents to acquire new knowledge developed by others and improves the chances of creating new knowledge through recombination. A burgeoning literature has provided strong evidence for the relatedness hypothesis, regardless of whether diversification is measured by the entry of new products, technologies, or industries, or analyzed in different geographical units (such as country, region, or city) (see, e.g., Boschma et al. 2013, 2015; Hidalgo et al. 2007; Neffke et al. 2011; Rigby 2015).

2.2 The role of general purpose technologies

The two mechanisms mentioned above suggest that the previous generation of technologies, especially those which are labeled as GPTs, given their two unique properties, is supposed to play a critical role in breeding the emergence of a new generation of technologies. First, GPTs are pervasive in nature, which means GPTs will be applied in a wide range of sectors and eventually penetrate every part of the economy (Bresnahan and Trajtenberg 1995). The far-reaching effects of GPTs are not only bound to technological progress, but also to changes in the behavioral pattern of the entire economy, leading to shifts in the "techno-economic paradigm" (Freeman and Perez 1988; Perez 2002). There are relatively few GPTs, but they represent the exemplary technologies behind industrial revolutions, such as the steam engine in the first industrial revolution, electricity in the second, and ICTs in the third (Helpman and Trajtenberg 1996). Second, GPTs will unlock complementary innovation opportunities for other sectors along with their diffusion processes (Bresnahan 2012). Technologies are interdependent and cumulative in nature, which means the availability of complementary technologies is a prerequisite for technologies being able to function or generate economic impacts (Rosenberg 1979). In some cases, recombination possibilities will only appear after a new technology is invented (Rosenberg 1979). As a GPT diffuses, it allows the actors in other sectors to recombine their existing technologies with the GPT and create new applications, leading to the reconfiguration and evolution of the user sectors' technological portfolios. For example, Fai and von Tunzelmann (2001) study the evolution of technological scale and scope by following the 32 largest inventing firms over 60 years and find that technological diversity is positively related to the emergence of new technological paradigms. Mendonça (2006, 2009) finds that the emergence of the ICT paradigm is a distinct force that drives traditional sectors to diversify into ICTs, not only as users but also as active knowledge producers.

2.3 Diffusion of ICTs as a digital base of AI

Building upon the two premises of GPTs, we argue that the diffusion of ICTs serves as the digital base for the emergence and development of AI. First, the diffusion of ICTs provides pervasive digital infrastructures for the adoption of AI. As indicated by Perez's (2002) model, in the early stage of the diffusion of GPTs, which she refers to as the "installation period," GPTs emerge as disruptive technologies and start to reshape the whole economic system by directing attention to new investment opportunities. One consequence of this period is the setting up of new infrastructure on a large scale, to exploit the GPTs more efficiently in the future. In the example of the adoption of ICTs, studies show that the energy infrastructure (electricity) plays a fundamental role, especially for low-income countries which face energy constraints (Aebischer and Hilty 2015; Armey and Hosman 2016). Due to the differentiated economic paths and industrial structures, regions differ substantially in terms of the infrastructures related to the previous technological paradigm, which will restrict future diversification possibilities. This "lock-in" effect may apply especially to less developed regions, which have limited recombination opportunities or are on the periphery of knowledge space. E-skills or e-competencies, or the general quality of human capital in a broader sense, constitute another important dimension of local capabilities that matter for the emergence of new technologies. Castellacci et al. (2020) show that e-skills, measured as the regional intensity of users or developers of ICTs, play a stronger role in regional technological diversification for less developed regions or regions with low levels of relatedness. Similarly, Cohen and Levinthal (1989, 1990) emphasize the importance of previous knowledge in understanding, assimilating, and utilizing external knowledge in innovation. This type of "absorptive capacity" is critical for the adoption of new knowledge. For example, based on survey data, a McKinsey report shows that about 75% of AI adopters (firms) rely on their existing digital knowledge and capabilities (Bughin and Van Zeebroeck 2018).

Second, the diffusion of ICTs unlocks new technological opportunities for AI and thus increases recombination possibilities for regional technological diversification. In the diffusion process, ICT sectors evolve at a high frequency of updates and iterations of technologies. Several technological shifts, for example from computer-dominant to internet/web services-dominant technologies, were observed in the past decades. The technological updates provide new opportunities for the users or downstream industries to create new innovational complementarities (Bresnahan and Trajtenberg 1995). For example, the rise of e-commerce or e-advertisement exhibits the penetration of ICTs to traditional sectors, like retailing and advertising industries. Meanwhile, the rapid evolution of ICTs opens new technological opportunities, acting as key enablers for the advancement of AI. A recent study by Montresor and Quatraro (2017) shows that a new generation of technologies plays a critical role in promoting regional technological diversification in European regions. They highlight that key enabling technologies not only augment the diversity of recombinant technologies but also unlock the recombination constraints. The recent upsurge of AI benefits, to a large extent, from the advances in machine learning, which in turn crucially depends on increasing computing power, high-speed connectivity, and the availability of large volumes of data (WIPO 2019). In this sense, ICTs can be regarded as a critical external knowledge source for AI, not only feeding new technologies but bridging possibilities for recombination.

3 Data and methodology

3.1 Data

The data we use are from the OECD REGPAT database (January 2020 edition[2]). The OECD REGPAT data have been geocoded and linked to regions across OECD and European countries (see, Maraut et al. 2008, for more details). This provides us with a unique opportunity to compare regional differences in terms of knowledge production of AI technologies. In addition, we use patent citation data from the OECD (July 2020 edition) to identify the knowledge sources of AI patents by tracing the citation flows.

[2] The REGPAT database (January 2020 edition) derives from the PATSTAT's (Worldwide Statistical Patent Database) EP Register (Spring 2020 version). The REGPAT database was not updated in the July 2020 version. We therefore use the January 2020 version.

The OECD REGPAT database comprises two types of datasets: patent applications to the EPO (European Patent Office) and patent applications under the Patent Cooperation Treaty (PCT). The PCT is an international patent system, which helps applicants to seek international patent protection. By relying on the patent data under the PCT, we could capture the patent applications with higher technical values because an international patent application usually involves much higher costs. This may also generate fewer country-based biases in the analysis of the cross-section comparison, considering that PCT is an international patent system (Tanner 2016).

3.1.1 Identifying AI patent applications

WIPO has recently developed and published a PATENTSCOPE Artificial Intelligence Index as a search model for AI patent applications (WIPO 2019, 2020). The index comprises key phrases, IPC (International Patent Classification), and CPC (Cooperative Patent Classification) codes and can be used as key search criteria for capturing AI technologies. The index is divided into two segments. The first segment contains CPC symbols that can be used independently to identify AI patent applications. The second segment contains key phrases that must be combined with IPC and CPC symbols. A study by Buarque et al. (2020) uses the EPO's PATSTAT database and a combination of keywords and CPC codes to identify AI patents. We use the CPC codes independently in our analysis to identify AI patent applications. We do this for two reasons: firstly, because classification codes can provide a more complete, efficient, and precise search compared to key phrases. Particularly, the CPC is an extension of the IPC and a more fine-grained scheme,[3] which may better capture the AI technologies that are scattered in different technological fields. The second reason is that we use the OECD REGPAT database which does not contain information on patents' text.

Based on the CPC codes listed in the index, we identified 13,781 unique AI patent applications under the PCT from 1980 to 2017,[4] accounting for about 4% of all applications during the period. Figure 1 displays the number of AI applications under the PCT over time. The figure shows that AI patent applications started to increase at a faster pace from the 1990s and attained an immense increase from 2012. The rapid growth from 2012 is attributed to the breakthroughs in machine learning, which benefitted from increasing computing power, data availability, and connectivity over recent years (WIPO 2019). To exhibit a more intuitive picture of the technological base of AI patent applications, we aggregate the frequency of CPC classes of AI technologies (within AI patent applications) into the 4-digit level (subclass level). In Table 1, we display the top ten technological fields[5] of AI technologies. Table 1 shows that AI technologies concentrate in the

[3] The CPC has about 250,000 classification entries while the IPC has about 70,000 classification entries.

[4] This analysis focuses on the period from 1980 to 2017 because, firstly, no AI patent application under the PCT is identified before 1980 in the REGPAT database and, secondly, this version of the REGPAT database only covers a small part of patent applications in 2018 and 2019 (priority year).

[5] We calculate the share of frequency of each 4-digit CPC class within all AI patent applications between 1980 and 2017. The top ten technological fields account for almost 90% of AI patent applications during the period.

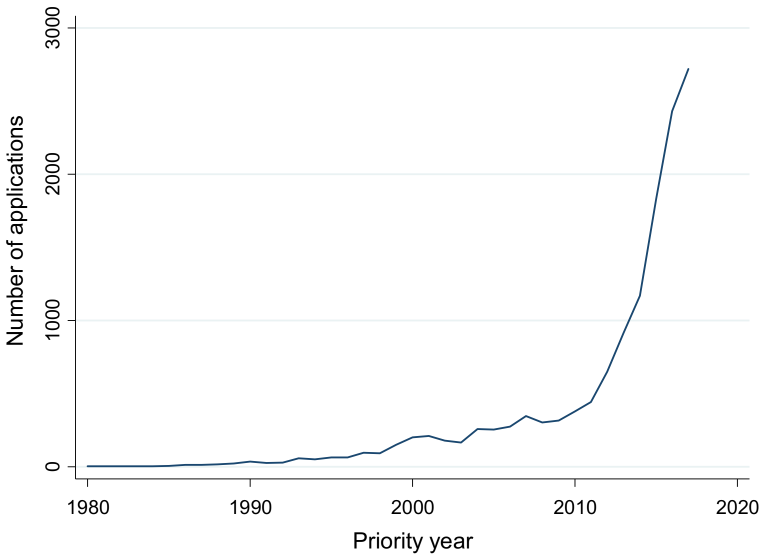

Fig. 1 The number of AI patent applications under the PCT over time

CPC class of instruments (3-digit level), such as technologies related to recognition of data, digital data processing, and computational models, which are related to basic AI techniques such as machine learning. We also find the presence of AI technologies in the technological areas where AI is applied in practice, such as computer vision, speech recognition, health, and transportation.

To assign the patents to regions, we could depend on the location information of either applicants or inventors. However, big firms (as one major group of patent applicants) usually register their patents under their headquarters (Maraut et al. 2008). Using the location information of applicants may therefore bias the geographical patterns of AI inventing activities. Thus, we use the location information of inventors to assign patents to regions. Since our study aims to identify and measure knowledge production/distribution based on the frequency of patent applications, instead of assessing the relative regional contribution of inventors from different regions, a non-fractional count of inventors is preferred when we assign patents to regions. We use this non-fractional count as a measure of AI inventing for each region, which means patent applications are counted every time for a region when an inventor is geolocated in this region. Only 8.5% of the 13,781 AI patent applications involve one inventor. About 90% involve 2–10 inventors. In terms of the geographical distribution of AI inventing, the top 20 countries account for over 96% of all AI patent applications under the PCT from 1980 to 2017, including the USA, Japan, China, Germany, South Korea, the UK, the Netherlands, Canada, France, Israel, Sweden, Australia, India, Switzerland, Spain, Singapore, Finland, Italy, Ireland, and Denmark.

Table 1 Top ten technological fields (4-digit CPC classes) of AI technologies for the period from 1980 to 2017. *Source of CPC description*: EPO

CPC	CPC subclass description (4-digit)	CPC class description (3-digit)	Share (%)
G06K	Recognition of data; presentation of data; record carriers; handling record carriers	Instruments	14.23
A61B	Diagnosis; surgery; identification	Health; amusement	14.14
G06F	Electric digital data processing	Instruments	11.86
G06N	Computer systems based on specific computational models	Instruments	11.41
G06T	Image data processing or generation, in general	Instruments	10.85
G05D	Systems for controlling or regulating non-electric variables	Instruments	8.08
B60W	Conjoint control of vehicle subunits of different type or different function; control systems specially adapted for hybrid vehicles; road vehicle drive control systems for purposes not related to the control of a particular subunit	Transporting	6.48
G10L	Speech analysis or synthesis; speech recognition; speech or voice processing; speech or audio coding or decoding	Instruments	5.50
B62D	Motor vehicles; trailers	Transporting	2.75
G05B	Control or regulating systems in general; functional elements of such systems; monitoring or testing arrangements for such systems or elements	Instruments	2.55

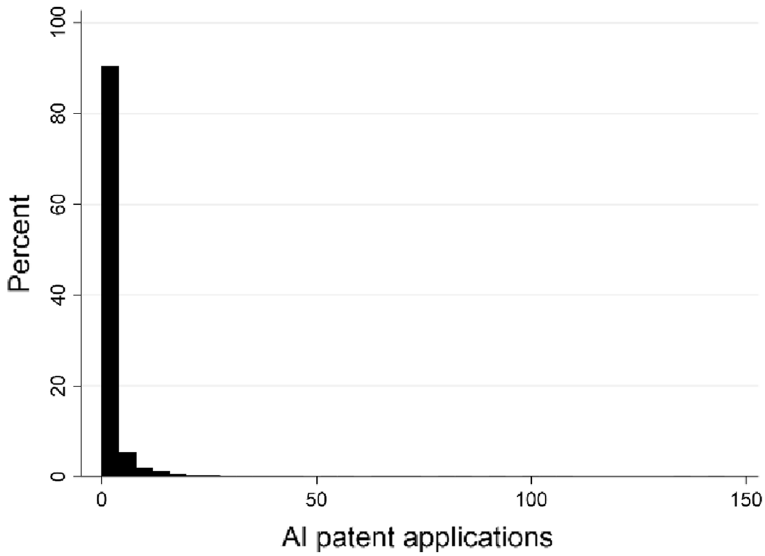

Fig. 2 Histogram of the number of AI patent applications in European regions

3.1.2 AI inventing in Europe

Since our main interest is in AI inventing in European regions, our analysis only includes the regions within EU27 + 3 countries.[6] As AI technologies are still in their early stage of development, our analysis starts from 1994 when AI technologies began to develop and diffuse at a faster pace (WIPO 2019). This yields 233 European regions (NUTS2 level) with AI inventing for the period from 1994 to 2017.[7] Figure 2 displays the histogram of the number of AI patent applications in European regions.[8] About 97% of the regions have less than 10 AI patent applications during the whole period. The distribution of AI inventing is highly skewed over time and space.

Figure 3[9] maps the number of AI patent applications across the European regions over four periods: 1994–1999; 2000–2005; 2006–2011; and 2012–2017. During the early period, there are only a limited number of regions with AI patent applications

[6] EU 27 + 3 countries include Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Portugal, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Romania, Slovakia, Slovenia, Spain, Sweden, plus the UK, Switzerland, and Norway.

[7] Some inventors are only assigned to a country but not an accurate region. We removed these inventors (61 inventors in 13 countries). The regions with no AI patent application during the whole period are not included, as we will use fixed-effects estimator in the econometric analysis.

[8] The observation is on a yearly basis.

[9] Since we use non-fractional counting when assigning patents to regions, Figs. 3 and 4 reflect the regional differences in the occurrence of patent applications instead of assessing the relative regional contribution of patent applications.

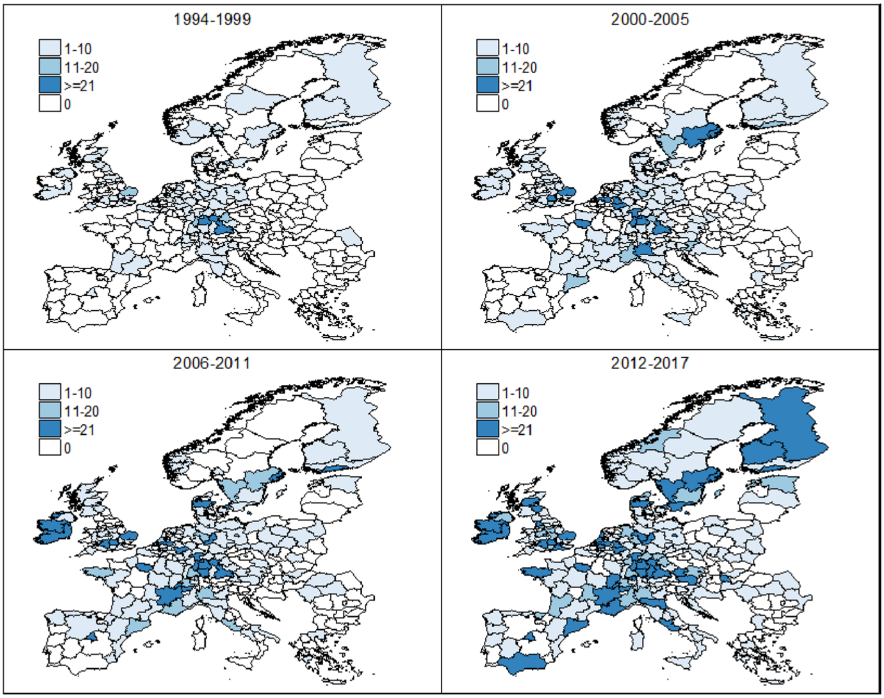

Fig. 3 The number of AI patent applications in European regions

and AI inventing concentrates in three German regions, namely Stuttgart (DE11), Oberbayern (DE21), and Mittelfranken (DE25). Over time, more regions engage in AI patent applications, especially during the period from 2012 to 2017, when 53 regions are found to have more than 20 AI patent applications. To exhibit the hot spots of AI inventing, we map the share of AI patent applications in European regions over the same periods (see Fig. 4). The hot spots of AI patent applications concentrate in a few regions in Western European countries, such as Germany, the Netherlands, and France. In the period from 2012 to 2017, the top five regions account for almost 40% of all AI patent applications, including North Brabant (NL41) in the Netherlands, Oberbayern (DE21) and Stuttgart (DE11) in Germany, Inner London (UKI1) in the UK, and Ile de France (FR10) in France.

3.2 Variables for econometric analysis

3.2.1 Dependent variable: measuring knowledge production of AI technologies

The main aim of this study is to examine the role of technological relatedness of ICTs in the emergence of AI technologies. We use the number of AI patent applications as the indicator of the production of AI technologies in a region. To avoid a situation where some regions may have a very small number of counts, we divide

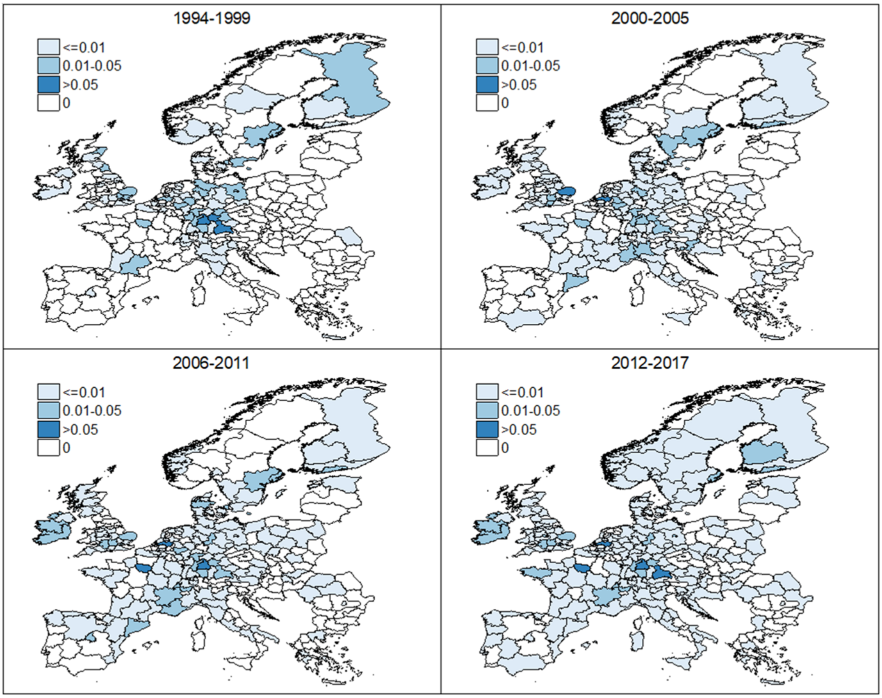

Fig. 4 The share of AI patent applications in European regions

the whole analysis period into eight subperiods[10] and use the sum of each subperiod of each region as the dependent variable. In this paper, we model a regional number of AI technologies as a function of the technological relatedness of ICTs. Compared to an entry model in which the probability of a new technological specialization is modeled as a function of the relatedness of focal technology to the local structure of existing technologies, this model could better capture the variation in regional AI knowledge production over time and how it is related to the local ICT base at the early development stage of AI.

3.2.2 Independent variable: measuring relatedness with existing technologies in a region

To indicate the technological relatedness of ICTs to a region's existing knowledge base, we develop a variable measured as the average density of relatedness of ICTs to a region's existing knowledge base. The variable is developed in two steps. We first calculate the proximity between all technologies. To this end, we conduct a co-occurrence analysis to measure the relatedness between technologies. This approach

[10] The eight sub-periods are: 1994–1996; 1997–1999; 2000–2002; 2003–2005; 2006–2008; 2009–2011; 2012–2014; and 2015–2017.

is developed by Hidalgo et al. (2007), which measures the proximity of products based on the likelihood of simultaneous occurrence of two exported products in a country, given the assumption that related products share similar factor endowments or capabilities. This approach has been widely adopted in previous studies on industrial diversification or regional branching (see, e.g., Cortinovis et al. 2017; Xiao et al. 2018; Boschma et al. 2013; Hausmann and Hidalgo 2010). A patent usually involves multiple classification codes to indicate the technological fields covered by the patent. We assume that all the co-classified technological fields share technological relatedness and their proximity to each other can be captured by the likelihood of their co-occurrence in a patent. We calculate the proximity among all technological fields (at the 4-digit IPC level[11]) by the likelihood of their co-occurrence in non-AI patent applications,[12] as shown in Eq. (1).

$$\varphi_{i,j,t} = \min\left\{P\left(x_{i,t}|x_{j,t}\right), P\left(x_{j,t}|x_{i,t}\right)\right\} \tag{1}$$

where φ indicates the proximity index. The index is the minimum conditional probability that a patent involves one technological field i, given that it involves another technological field j. The second step is to link the proximity index to a region's existing knowledge base. A region's knowledge base is indicated by the collection of technological fields in its patent portfolio. Again, to avoid potential endogeneity, we exclude all AI patent applications when identifying a region's existing knowledge base. The average density of relatedness of ICTs to a region's existing knowledge base is calculated as shown in Eq. (2).

$$\overline{d_{i,r,t}} = \left(\frac{\sum_k \varphi_{i,k,t} x_{k,r,t}}{\sum_k \varphi_{i,k,t}}\right) \tag{2}$$

where the subscript i or k refers to a technological field; $x_{k,r,t}$ is a dummy variable to show whether technology k is present in region r at year t. $d_{i,r,t}$ is the density of technology i in region r at year t, calculated as the sum of proximities of technology i to all technologies that are present in region r at year t divided by the sum of proximities of technology i to all technologies. The density varies between 0 and 1. A higher density means a higher level of relatedness of technology i to the technologies that are present in region r. Finally, we take the average density of all ICTs for each region. We use a broad definition of ICTs to calculate the average density of relatedness of ICTs to a region's existing knowledge base. The definition of ICTs is elaborated in Sect. 4.1.

[11] IPC is used here because most existing definitions of ICT are based on IPC classifications.

[12] We exclude AI patent applications to avoid potential endogeneity biases.

4 Analyses and results

4.1 Knowledge sources of AI patents

As a newly emerging technology, the development of AI may draw upon various sources of established knowledge. To identify the knowledge sources of AI patents, we rely on citation analysis, where the patent citation data are used as a proxy to measure knowledge flows or spillovers (Jaffe and Trajtenberg 1998; Jaffe et al. 2000). To quantify the relative intensity of knowledge flows among different sources, we use the technology classification to group the technological fields of the patents that were cited by the AI patents.

The classification we use is mainly based on the typology developed by Schmoch (2008, updated in 2019), which groups all patentable technological fields into five general categories (based on IPC classification): electrical engineering; instruments; chemistry; mechanical engineering; and other fields. Electrical engineering further constitutes eight subcategories, including electrical machinery, apparatus, and energy; audio-visual technology; telecommunications; digital communication; basic communication processes; computer technology; IT methods for management; and semiconductors. To capture the role of ICTs in a broader sense and the ICTs at the technological frontier, respectively, we use two definitions of ICTs in the citation analysis: the broad definition (defined as the category of electrical engineering excluding the subcategory of electrical machinery, apparatus, and energy) and the restrictive definition (defined as those ICTs that are categorized into high technology by Eurostat (2006), including computer and automated business equipment, semiconductors, and communication technology). Accordingly, we revise Schmoch's typology into six general categories in our analysis:

- electrical machinery, apparatus, energy,
- ICTs (broad definition)
- instruments,
- chemistry,
- mechanical engineering,
- other fields.

More than 88% of the IPC classes defined by the restrictive definition of ICTs fall within the broad definition of ICTs. The rest concentrate in the IPC class of "B41J," which is grouped into the category of mechanical engineering in Schmoch's typology. In our analysis of AI patent applications, the restrictive definition is a subset of the broad definition because no cited technological field falls within "B41J."

To measure the intensity of knowledge flows between technological categories and AI, we calculate the share of citations: the cited number of each technological category divided by the total cited number. We report the results over four periods: 1994–1999; 2000–2005; 2006–2011; and 2012–2017 in Table 2.[13] The two major

[13] To be able to compare the citation patterns between periods, we include the cited patents that were published in the previous 11 years for each period. For example, for the period from 1994 to 1999, we

Table 2 The share of the cited number of each technological category by AI patent applications

	Electrical machinery, apparatus, energy	ICT		Instruments	Chemistry	Mechanical engineering	Other fields
		Broad	Restrictive				
1994–1999							
Cited number	4	73	35	94	3	21	11
Share	2%	35%	17%	46%	1%	10%	5%
2000–2005							
Cited number	24	222	94	232	17	41	10
Share	4%	41%	17%	42%	3%	8%	2%
2006–2011							
Cited number	46	350	205	391	21	116	23
Share	5%	37%	22%	41%	2%	12%	2%
2012–2017							
Cited number	59	1434	832	1195	86	457	71
Share	2%	43%	25%	36%	3%	14%	2%

Table 3 Variable description and summary statistics

Variables	Description	Obs	Mean	Median	Std. Dev	Min	Max
AI_inventing	The number of AI patent applications	1,864	4.34	0	17.47	0	335
Ave_density	The average density of technological relatedness	1,864	0.28	0.24	0.23	0	0.94
Pop	Population	1,661	14.27	14.27	0.68	12.40	16.30

There are missing values for the variable of the population, which is due to the changes to the NUTS classification systems over time

knowledge sources of AI patent applications are instruments and ICTs (broad definition). For AI patent applications from 1994 to 1999, the share of the cited number is 46% for instruments and 35% for ICTs (broad definition). The share of ICTs (restrictive definition) is 17%. Over time, the relative importance of ICTs (measured by both the broad definition and restrictive definition) increases. At the same time, the

Footnote 13 (continued)
include cited patents that were published between 1989 to 1999. This analysis includes all AI patents identified in the PCT database.

share of instruments decreases. For AI patent applications from 2012 to 2017, ICTs have become the largest knowledge source of AI patent applications. About 43% of cited technologies are from the category of ICTs (broad definition). During the same period, the share of ICTs (restrictive definition) increased to 25%. This indicates the increasing importance of a digital base for the recent development of AI, which is consistent with the recent trend in AI patenting where machine learning has been predominating in the patent applications related to AI techniques and AI-related patents (WIPO 2019).

4.2 The effects of technological relatedness of ICTs

We conduct an econometric analysis to test how technological relatedness of ICTs to a region's existing knowledge base influences regional knowledge production of AI inventing. The final dataset for the econometric analysis is a balanced panel covering 233 European regions over eight periods. Table 3 presents the variable description and descriptive statistics. Table 10 in Appendix shows the correlation matrix between the variables. In addition to the dependent and independent variables, we include a control variable of the population to account for regional differences in size that change over time. Since the dependent variable is the number of AI applications, we expect a positive relationship between population size and the regional number of AI patent applications. The population data are from Eurostat. There are missing values for the variable of population because of the changes to the NUTS classification systems over time.[14] Moreover, we include the dummy variables for time periods to control for the time effects in general. The independent variable and the variable of the population are measured 1 year before the starting year of each period. In our dataset, about 53% of observations have no AI inventing and the distribution of AI inventing is highly skewed.

Since the dependent variable is the number of AI patent applications, we use the count model to model the effects of technological relatedness on the number of AI patent applications. Fixed effects are used to account for unobserved heterogeneity that is constant over time at regions. Since our data suffer from the problem of overdispersion (the variance is higher than the mean), this suggests a negative binomial model. However, many studies indicate that the method for (conditional) fixed-effects negative binomial regression, which many statistical software products (such as Stata) depend on, is not valid because it fails to control for unchanging covariates (Allison and Waterman 2002; Greene 2005; Guimarães 2008). Following the suggestion by Allison (2012), we use the unconditional fixed-effects negative binomial model by including dummy variables for each region as our benchmark estimation model.

To facilitate interpretation, we standardize technological relatedness and population in the regressions. The results are reported in Table 4. In Specification (1), we

[14] The changes to the NUTS classification systems over time make it difficult to consistently trace the regional statistics over a long period of time for the regions which are affected. This is one reasons why we do not include more regional-level control variables as there will be many missing values.

Table 4 The effects of technological relatedness of ICTs on AI inventing

Variables	(1)	(2)	(3)	(4)
Ave_density	1.618***	1.242***	0.479***	0.504***
	(0.0923)	(0.101)	(0.110)	(0.117)
Pop (log)		5.630***		1.322**
		(0.667)		(0.661)
Constant	−0.356	−0.209	−1.211***	−0.554***
	(0.477)	(0.450)	(0.429)	(0.0868)
Obs	1,864	1,661	1,864	1,661
Region fixed effects	Yes	Yes	Yes	Yes
Period dummies	No	No	Yes	Yes
Log likelihood	−3081.0321	−2723.1711	−2884.9414	−2581.6304
LR chi2	1491.38	1424.67	1883.56	1707.75
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

only include the main predictor; in Specification (2), we add population as the control variable; in Specification (3), we include period dummies; and in Specification (4), we include all the independent variables.

The coefficient of the negative binomial model is interpreted as the expected difference in the logs of expected counts of the dependent variable given one-unit change of the independent variable, while all the other variables are held constant. From Specification (1), we find that if the average density of technological relatedness of ICTs was to increase by one unit, the expected difference in the logs of expected counts of AI patent applications would increase by 1.618 units. The significant coefficient reveals a positive effect of the average density of technological relatedness of ICTs on regional AI inventing. In Specification (2), when we include the control variable of population, the positive relationship between technological relatedness and regional AI inventing is still significant, although the magnitude decreases slightly. For the control variable, as expected, we find a significantly positive effect of population on AI inventing. In Specification (3), when we include the dummy variables for time periods, the positive coefficient of technological relatedness is still statistically significant, but the magnitude decreases by about two thirds. In Specification (4), when we include both the population and time dummy variables, the technological relatedness of ICTs still shows a statistically positive effect on regional AI inventing. The results show that technological relatedness of ICTs to a region's existing knowledge base is an important predictor for AI inventing in European regions. However, the effect of technological relatedness on AI inventing is reduced when the time effects are accounted for.

Compared to the other global players, such as the USA and China, Europe has been lagging regarding investing in the first waves of AI and related technologies (European Commission 2018; WIPO 2019). As shown in Fig. 3 in Sect. 3.1, most AI inventing concentrates in a few German regions in the early period. However, the diffusion of AI technologies has been accelerating recently, especially since 2012. Many European

Table 5 The catch-up effects of technological relatedness of ICTs on AI inventing

Variables	≥ 5	≥ 10	≥ 15
Ave_density	0.328***	0.391***	0.419***
	(0.113)	(0.111)	(0.110)
Ave_density*catchup	2.050***	2.409***	2.897***
	(0.380)	(0.550)	(0.740)
Constant	− 1.173***	− 1.182***	− 1.187***
	(0.423)	(0.424)	(0.425)
Obs	1,864	1,864	1,864
Region fixed effects	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Log likelihood	− 2865.9461	− 2871.3893	− 2873.513
LR chi2	1921.55	1910.67	1906.42
Prob > chi2	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

regions have been catching up, reflected by the increase in AI patent applications and the spread of AI inventing to more European regions. To examine whether there are any catch-up effects of technological relatedness of ICTs, we create a dummy variable (*catchup*), with one indicating the regions that transit from having no AI patent applications in the early period (1994–2005) to having AI patent applications in the recent period (2006–2017). We include an interaction term between *Ave_density* and *catchup* to indicate the catch-up effects. Because there are many missing values for the variable of the population, we use Specification (3) in Table 4 as the baseline model. To test the robustness of the results, we use different thresholds to determine whether it is a catch-up region. The results are reported in Table 5.

As reported in Table 5, the coefficient of *Ave_density*catchup* indicates the catch-up effect of technological relatedness of ICTs on AI inventing. The first column displays the results when the catch-up regions are identified as those with no AI patent applications in the period from 1994 to 2005 but with at least five AI patent applications in the period from 2006 to 2017. The significant coefficient of the interaction term shows a strong positive catch-up effect of technological relatedness of ICTs. The effect of technological relatedness on AI inventing decreases slightly but is still significant. In the second and third columns, we test the results by using different thresholds for defining catch-up regions. The coefficients of interaction terms are both significantly positive and the magnitude increases as the threshold increases. The results show that ICTs are an important enabler for regions that caught up regarding AI inventing. The catch-up effects seem to be stronger for regions that caught up fast.

5 Robustness check

In the econometric analysis, we use the average density of relatedness of ICTs to a region's existing knowledge base to indicate the regional knowledge base of ICTs. To check whether our main findings are sensitive to a different measure of

Table 6 Robustness check: related variety within ICTs as the independent variable

Variables	Benchmark model	Catch-up effects		
		≥ 5	≥ 10	≥ 15
RV	0.135**	0.118*	0.102*	0.119**
	(0.0581)	(0.0617)	(0.0601)	(0.0589)
RV*catchup		0.136	0.464**	0.525
		(0.170)	(0.229)	(0.337)
Constant	− 1.240***	− 1.237***	− 1.233***	− 1.232***
	(0.417)	(0.418)	(0.418)	(0.418)
Obs	1,591	1,591	1,591	1,591
Region fixed effects	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Log likelihood	− 2748.2313	− 2747.9047	− 2745.9997	− 2746.8949
LR chi2	1670.23	1670.89	1674.70	1672.91
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

the independent variable, we employ an alternative indicator, related variety within ICTs for a robustness check. Related variety is a measure to capture both relatedness and variety across activities in a region. The literature on regional innovation has widely discussed the role of related variety, such as related industries, in providing opportunities for recombination of knowledge and facilitating regional innovation and growth (Frenken et al. 2007; Neffke et al. 2011; Boschma et al. 2013). Following Frenken et al. (2007), we calculate related variety within ICTs as the weighted sum of entropy at the level of five-digit IPCs within each three-digit IPC within ICTs, as shown in Eqs. (3a) and (3b).

$$RV = \sum_{s=1}^{S} P_s H_s \tag{3a}$$

$$H_s = \sum_{i \in s} \frac{P_i}{P_s} \log_2 \left(\frac{1}{P_i / P_s} \right) \tag{3b}$$

where the subscript i denotes a five-digit IPC which is exclusively under a three-digit IPC s; P refers to the share of patent applications; and H_s refers to the five-digit variety within each three-digit IPC. We re-estimate the benchmark model and the models with interaction terms based on different thresholds. The results are reported in Table 6.

From Table 6, we find that related variety within ICTs shows a significantly positive effect on AI inventing, even though with a lower magnitude than the technological relatedness of ICTs. The catch-up effects are only significant when the threshold is set up at ≥ 10. One explanation is that the variable of related variety within

Table 7 Robustness check: based on the restrictive definition of ICTs

Variables	Benchmark model	Catch-up effects		
		≥ 5	≥ 10	≥ 15
Ave_density	0.381***	0.207*	0.283**	0.321***
	(0.112)	(0.115)	(0.113)	(0.112)
Ave_density*catchup		1.871***	2.176***	2.503***
		(0.337)	(0.487)	(0.657)
Constant	− 1.257***	− 1.223***	− 1.231***	− 1.234***
	(0.430)	(0.423)	(0.425)	(0.426)
Obs	1,864	1,864	1,864	1,864
Region fixed effects	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Log likelihood	− 2888.582	− 2868.3952	− 2874.5569	− 2877.939
LR chi2	1876.28	1916.66	1904.33	1897.57
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

ICTs tends to capture the general composition of a knowledge base within ICTs. By contrast, the variable of regional relatedness of ICTs tends to capture the specific relatedness between ICTs and the local knowledge base. Another explanation is that we have many regions with missing values for the variable of related variety within ICTs. These regions have a limited number of ICTs and thus no variation in the share of patent applications between 3-digit IPC and 5-digit IPC. The reduced number of observations may lead to the insignificance of results in some specifications. Yet, even with the reduced number of regions, the sign of the catch-up effect is still positive across the specifications with different thresholds and the magnitude tends to increase as the threshold increases.

Recall that we use the broad definition to define ICTs when calculating the technological relatedness in Sect. 3.2. This may raise a concern about whether our findings are sensitive to a change in the definition of ICTs. To address this concern, we use the restrictive definition of ICTs for a robustness check. We re-estimate the effects of technological relatedness of ICTs without the interaction term, with the interaction term based on different thresholds, respectively. The results, displayed in Table 7, show that our main findings hold. When we use the restrictive definition of ICTs, both the magnitudes of technological relatedness and the catch-up effects are relatively smaller than when ICTs are based on a broad definition. This may indicate that what matters for the emergence and catch-up of AI inventing resides more in the ICTs in a broad sense than those advanced ICTs.

As discussed in Sect. 3.1, we use non-fractional counting to assign patents to regions in the main analysis. A potential concern is whether our findings are sensitive to the choice of the counting method. To address this concern, we use fractional counting of AI patent applications for a robustness check. When using fractional counting, the number of AI patent applications is a fraction. To decide whether it is a catch-up region, we use three different thresholds to measure the

Table 8 Robustness check: based on fractional counting of AI patents

Variables	Benchmark model	Catch-up effects		
		≥ p25th	≥ p50th	≥ p75th
Ave_density	0.323***	0.233**	0.256**	0.300***
	(0.0985)	(0.1000)	(0.0995)	(0.0986)
Ave_density*catchup		1.650***	1.685***	2.885**
		(0.408)	(0.487)	(1.298)
Constant	− 1.654***	− 1.639***	− 1.643***	− 1.650***
	(0.422)	(0.421)	(0.421)	(0.421)
Obs	1,864	1,864	1,864	1,864
Region fixed effects	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Log likelihood	− 1696.0398	− 1685.9717	− 1688.4793	− 1692.1762
LR chi2	2153.85	2173.99	2168.97	2161.58
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 9 Robustness check for the catch-up effects: including the variable of the population

Variables	≥ 5	≥ 10	≥ 15
Ave_density	0.344***	0.418***	0.448***
	(0.120)	(0.118)	(0.117)
Ave_density*catchup	1.908***	2.174***	2.608***
	(0.377)	(0.549)	(0.759)
Pop (log)	1.490**	1.366**	1.393**
	(0.669)	(0.663)	(0.662)
Constant	− 0.990**	− 1.007**	− 1.011**
	(0.418)	(0.420)	(0.421)
Obs	1,661	1,661	1,661
Region fixed effects	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Log likelihood	− 2565.1502	− 2570.7958	− 2572.9098
LR chi2	1740.71	1729.42	1725.19
Prob > chi2	0.0000	0.0000	0.0000

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

number of AI applications in the recent period, ≥ p25th (the 25th percentile of the number of AI applications), ≥ p50th, and ≥ p75th. The results are shown in Table 8, showing that our main findings hold.

Because the variable of the population has missing values, to make use of all the observations, the model we use to test the catch-up effects in Table 5 does not include the variable of population. To test the robustness of catch-up effects with the population variable, we re-estimate Table 5 by including the population variable. The results, displayed in Table 9, show that our findings in terms of catch-up effects hold.

6 Discussion and conclusion

Through the lens of regional technological diversification, this paper focused on two specific research questions: how important ICTs are for the emergence of AI technologies and how a regional knowledge base of ICTs influences the knowledge production of AI in European regions. Based on the patent data from the OECD REGPAT database, our findings show that ICTs are a major knowledge source of AI technologies and that their importance has been increasing over time. We also find that technological relatedness of ICTs to a region's existing knowledge base is an important predictor of the emergence of AI inventing in European regions. Especially, the effects of technological relatedness of ICTs are stronger for regions which have recently caught up regarding AI inventing. Our findings suggest that the local infrastructure and capabilities of ICTs serve as the digital base for the emergence and development of AI in European regions. Meanwhile, the development of ICTs itself also unlocks new technological possibilities. Both effects display the enabling nature of GPTs not only feeding new technologies but bridging possibilities for recombination.

The contribution of this paper is threefold. First, our study theoretically contributes to the literature on evolutionary economic geography by providing new insights into how regional branching is influenced by the diffusion of GPTs. Although technological relatedness and GPTs have been emphasized separately as key tools for smart specialization policy (S3) (Boschma and Giannelle 2014; Foray et al. 2009), few studies have investigated how GPTs influence regional diversification and development through the mechanism of technological relatedness. Montresor and Quatraro's (2017) study is one exception, which explores the role of GPTs in regional branching. They focus, however, on GPTs as a group of new generation key enabling technologies. This raises the question of whether the new emerging technologies can fully capture the two properties of GPTs. Our findings suggest that the role of ICTs may go beyond the advanced technologies but resides more in ICTs in a broader sense. Furthermore, our findings suggest that future studies could go beyond the few key enabling technologies and adopt a more holistic view to investigate the successive nature of technological evolution. In addition, we used citation analyses to exhibit how important ICTs are as one knowledge source of AI and how their importance changes over time.

Secondly, our study methodology contributes to the literature on regional diversification. In the recent studies that focus on regional diversification processes of newly emerging technologies, technological relatedness is usually measured as the proximity of focal technologies to the local structure of existing technologies. The proximity between technologies is specified by a "technology space," which is usually developed based on the frequency of the co-occurrence of technologies in a specific relation, such as co-location in a region or co-classification in a patent. This approach is useful when the focal technologies are stable and mature. However, it may be limited when it is used to measure the relatedness of radically newly emerging technologies, particularly when they are still in the early stage of development. For example, the definition of AI is still fuzzy and has been updated along with the fast development of the field (EPO 2017; WIPO 2019). In the case of patents, the patent classification codes, such as IPC and CPC, might not have been updated to take full account of emerging technologies. In this sense, the focus on only the relatedness of AI technologies in the current knowledge network may not capture the full picture of its diversification process, as the proximity may not be stable enough to capture the full picture between AI and other technologies. In our study, instead of focusing on the role of regional knowledge bases of AI, we pay attention to the role of the regional knowledge base of ICTs. It is not only a relevant technology for AI inventing but also a mature GPT, which is more stable for capturing regional knowledge bases. This may provide a new view for those studies that aim to investigate the role of relatedness in the regional branching of emerging technologies.

Third, our findings also suggest some policy implications. As discussed above, our findings suggest that future regional policies may consider going beyond advanced enabling technologies and paying attention to the role of GPTs in a broader sense in regional development. In addition, past European regional policies on digital technology and AI have developed in parallel with one other (European Commission 2016, 2018). For example, e-infrastructure has been addressed in the policies promoting the EU's digital future (European Commission 2016) and AI technology separately (European Commission 2018). Our findings indicate a close and successive relationship between digital technology and AI and thus suggest many initiatives or investment opportunities could be jointly coordinated and designed in future policies.

One limitation of this study is that we cannot include more time-varying regional controls. The regional-level statistics are usually not available for a long time period or are difficult to trace consistently over a long time period due to the changes in classification systems of regions. This makes it difficult to include more regional-level control variables than the variable of the population in our analysis. Even though we believe the population is a key regional indicator, which could capture or be correlated to the major time-varying regional differences, it is still possible that the results of our analysis are biased due to the omitted time-varying regional variables.

The new wave of technological change gives new momentum to the field of evolutionary economic geography. It may not only generate new academic debates in terms of how regions embrace the opportunities and challenges arising from the new technologies, but also influence the policy approach to integrate the role of technological change in future policy design. We hope this study will attract further studies to improve our understanding of the micro foundation of how GPTs influence regional diversification.

Appendix

See Table 10.

Table 10 Correlation matrix of variables

Variables	(1)	(2)	(3)
AI_inventing (1)	1		
Ave_density (2)	0.3791	1	
Pop (3)	0.2019	0.3746	1

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