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The 'picking the fittest' approach and spatial dynamics in China's artificial intelligence regional development

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ABSTRACT

This paper investigates the role of regional specialization in ICT in fostering AI patenting performance and inter-regional spatial spillovers across China's provincial-level regions. Using panel fixed effects estimators, a Spatial Autoregressive Regression model and by adapting the technological frontier IV strategy on a comprehensive database covering 2006–2021, we find that positively selecting areas where regional ICT specialization is leveraged – the "picking the fittest" approach – can increase AI patenting performance while exacerbating regional disparities. Furthermore, we find that geographical proximity to developed AI regions impedes AI patenting progress in neighboring areas. The findings highlight the need for collaborative regional strategies and urge policy-makers to achieve a balance between strengthening regional specialization and promoting cooperation.

1. Introduction

Spatial spillovers significantly influence regional innovation dynamics and economic development (Antonelli and Colombelli, 2017). The recombination of existing local knowledge and capacities leads to the emergence of new technological activities and innovation (Frenken and Boschma, 2007). However, research on regional innovation tends to consider regions as isolated entities, neglecting inter-regional spillovers (Boschma et al., 2017). While empirical research in different European contexts has highlighted that knowledge diffusion is geographically constrained, confirming the importance of agglomeration effects and their diminishing effects with distance (Moreno et al., 2005; Lehmann and Menter, 2018), few studies have focused on the negative aspects of such agglomeration and inter-regional knowledge diffusion (Wang et al., 2022). For instance, Montmartin et al. (2018) investigated the effect of policy mix on private R&D investments and found significant negative spatial dependence among R&D investments. This leads to resource crowding and market rivalry forcing regions to focus more on out-competing their neighbors rather than engaging in cooperative innovation efforts (Bloom et al., 2013).

This is particularly relevant in the case of artificial intelligence (AI). The need to pursue market dominance in many AI-related sectors such as deep learning and robotics has generated a competitive race (Cockburn et al., 2019), not to mention AI's high reliance on data, providing a significant competitive advantage to those capable of collecting, analyzing, and utilizing it (Klingenberg et al., 2019). At the regional level, AI has the potential to drive technological diversification by enabling the recombination of complex knowledge, thereby allowing regions to develop and sustain new specializations over time (Montresor and Quatraro, 2017). This process hinges on the ability of AI to integrate diverse local knowledge bases, reinforcing the role of regional capabilities in fostering innovation (Bresnahan, 2010; Brynjolfsson et al., 2018).

Despite this potential, the extent to which AI-driven agglomeration yields positive regional outcomes remains underexplored. While research at the European level acknowledges the broader implications of Industry 4.0 technologies, of which AI is a part, and AI on regional economies, more in-depth investigations are required to assess its long-term effects (De Propris and Bailey, 2021). In particular, current empirical analysis on AI-related clustering makes it difficult to determine whether such concentrations foster sustainable growth or exacerbate regional inequalities (De Propris and Bellandi, 2021). Furthermore, the geography of Industry 4.0 technologies remains highly uneven, with regional capabilities playing a decisive role in determining whether regions can successfully integrate into new knowledge production networks (Balland and Boschma, 2021). Given these disparities, policy

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interventions are crucial to supporting regional adaptation, ensuring that AI-driven value creation benefits local productive factors and resources through multi-actor engagement (Labory and Bianchi, 2021).

Building on these insights, a critical gap remains in understanding the precise mechanisms through which AI agglomeration influences regional development. While existing research has explored the uneven geography of Industry 4.0 and the role of regional capabilities in technological change, it remains uncertain whether AI clusters foster sustainable innovation or instead deepen regional inequalities. Additionally, while policy interventions are widely recognized as crucial for regional adaptation, further research is needed to identify the most effective governance strategies for ensuring that AI-driven innovation benefits a diverse set of regions rather than concentrating in a few highly specialized hubs. To address these gaps, this research examines the following research questions: what are the effects of previous knowledge base specialization, positive selection, and inter-regional spillovers in the development of AI innovation?

We use the Chinese case as an empirical setting to address the research questions. China has set clear and ambitious goals to become a leading global innovator in AI (State Council of the PRC, 2017). These efforts are evident not only in the prominent role of the Chinese government with its numerous AI-related policies (Yang and Huang, 2022) but also in the interplay of different actors like government institutions, universities, and industry (Jacobides et al., 2021). One of China's key strategies for developing AI is the "National New Generation Artificial Intelligence Innovation and Development Pilot Zones" (hereafter "AI zones") policy, introduced by the Ministry of Science and Technology (Ministry of Science and Technology of the PRC MOST, 2019) in 2019. These AI zones were designed to leverage local assets and foster AI development at a national scale. The policy's ambition is twofold: to enhance AI capabilities at the regional level and to drive overall national AI technological progress.

However, China's AI innovation strategy faces significant obstacles in achieving balanced regional growth. One concern is the inherent bias in China's policy experimentation processes. Many pilot projects are implemented in economically advanced regions where local leaders, driven by short-term political incentives, may exert extra effort during the pilot phase, but the long-term sustainability of these initiatives remains uncertain (Wang and Yang, 2021). This "picking the fittest" strategy has the potential to widen existing disparities by reinforcing the competitive advantage of leading regions while sidelining less developed ones. Moreover, differences in institutional proximity across neighboring regions can limit inter-regional knowledge spillovers, thereby further hindering innovation diffusion and deepening regional disparities (He et al., 2019; Xie et al., 2023). These dynamics can result in "club convergence," where regions with similar initial conditions cluster together, exacerbating technological and economic inequalities (Jimenez-Moro et al., 2023; Rui et al., 2023).

This pattern highlights a paradox within China's national AI strategy: while fostering regional hubs can promote advanced specialization, it may inadvertently hinder collaborative spillovers necessary for sustained innovation development (Bloom et al., 2013; Montmartin et al., 2018; Wang et al., 2022). Understanding this tension is essential for aligning regional AI initiatives with China's broader innovation goals. Despite extensive research on China's national AI strategy and its global ambitions, the regional dimension remains underexplored. Prior studies have primarily focused on the national innovation system, focusing on the role of major corporations (Jacobides et al., 2021), the triple helix model of government-industry-university collaboration (Arenal et al., 2020), and the global interconnections driving AI growth (Yu et al., 2022). However, since the introduction of the "2006 Medium and Long-Term Plan for Science and Technology Development" (Liu et al., 2011), China's strategy has increasingly emphasized regional innovation, particularly through provincial-led programs (Heilmann et al., 2013; Sun et al., 2018).

Therefore, the objective of this paper is twofold: first, to investigate the contribution of past knowledge specialization in enhancing AI patenting performance in AI zones; and second, to comprehend the impact of inter-regional spillovers in the context of AI technologies in China.

To address these goals, we construct a database encompassing Chinese provincial-level region data spanning the period from 2006 to 2021. Using a linear panel regression with fixed effects estimators, a Spatial Autoregressive model, and by adapting Acemoglu and Restrepo's (2020) technological frontier Instrumental Variable strategy, we show that the AI zone program significantly strengthens regional AI patenting performance and it emphasizes the effects of a "picking the fittest" strategy. This essentially means that China selected the regions with specific capabilities and pushed them even further by simultaneously accentuating regional disparities in AI patenting. Moreover, geographical proximity to regions with developed AI patenting may hinder the progress of neighboring regions. To mitigate these effects, we recommend policies that enhance the absorptive capacity of lagging regions through investments in education, R&D infrastructure, and institutional reforms, while encouraging more collaborative, cross-regional innovation initiatives. Creating AI Regional Collaborative Hubs could help align regional capabilities with national innovation objectives, reducing the inefficiencies of competitive spillovers and fostering inclusive growth across China's AI landscape.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature and the theoretical background and formulates the appropriate research hypothesis. Section 3 describes the data and methodology. Section 4 presents the analyses and the findings. Section 5 discusses the results, provides the scholarly and policy implications, and concludes the paper by offering areas for future research.

2. Literature background

2.1. Regional specialization, local experimentation and positive selection

Previous studies set in Europe and in the USA have found that regions that built solid foundations during earlier technological waves are better equipped to drive technological breakthroughs (Boschma et al., 2015; Laffi and Boschma, 2022). In particular, strong information and communication technologies (ICT) infrastructures can lead to AI development (Xiao and Boschma, 2022). Advanced manufacturing hubs with strong prior capabilities in ICT and Industry 3.0 are also more likely to adopt AI, as seen in the concentration of Industry 4.0 technologies in these areas (Corradini et al., 2021). At the heart of this process is the concept of recombinant growth, where innovation does not arise in isolation but from the recombination of existing knowledge and technologies (Weitzman, 1996, 1998). This aligns with the broader understanding of regional innovation studies, where new technological activities build on existing capacities and local knowledge base (Frenken and Boschma, 2007). Beyond their technological assets, these regions benefit from cognitive proximity, which enhances their ability to absorb and recombine knowledge and apply AI innovations effectively (Cohen and Levinthal, 1990). Thus, the relationship between prior technological capabilities and new innovations is not just a matter of resources but also of how well regions can recombine existing knowledge into new, productive uses.

The regional variation in technological capabilities helps to explain the uneven distribution of AI innovation across different regions in China. China's strategy for AI development heavily relies on the capacity of local governments to foster innovation, particularly through policy experimentation and the strategic selection of regions with strong technological foundations (Wang and Yang, 2021). The government's approach is rooted in selecting these regions, granting them autonomy to experiment with AI applications. This decentralized model leverages regional strengths to fuel national technological progress (Liu et al., 2022). This can lead to significant heterogeneity in the performance of science and technology parks in China, where regions with advanced technological infrastructures form elite innovation clusters that

consistently outperform others (Rui et al., 2023).

Moreover, China's economic development, particularly in key industries, has long been tied to regional policy initiatives (Li, 2015). Economic and Development Zones (EDZs) and High-Tech Development Zones (HTDZs) are prominent examples of regional policy implementations. EDZs focus on developing extra-local linkages, while HTDZs prioritize establishing domestic R&D institutes and collaborations for indigenous-based R&D (Howell, 2019). Recent evidence suggests that EDZs enhance economic growth through industrial clusters and improved firm performance (Liu et al., 2020), but they may not always generate high-quality growth at the regional level (Ma et al., 2023). In contrast, HTDZs generate learning effects and Marshallian-based externalities (Howell, 2019). China's focus on AI has further amplified these efforts, as the government introduced cluster policies, industry enabler policies, and knowledge diffusion initiatives. The "AI zone" policy issued by the MOST in 2019 aims to establish 20 pilot zones by 2023, each of which will demonstrate replicable AI applications for the nation's overall benefit (Wu et al., 2020). These zones are selected based on certain criteria, including a region's past innovation capacity and their capabilities as ICT and AI innovators, among others. This positive selection process ensures that only the most technologically capable regions receive resources, maximizing the likelihood of success in AI adoption (Wang and Yang, 2021).

The AI zone policy exemplifies China's hybrid implementation model, combining centralized oversight with decentralized, region-specific execution. By reinforcing local embeddedness in AI innovation, this approach ensures that the most capable regions lead in AI while contributing to national technological advancement (Liu et al., 2022). China's AI development strategy is centered on selecting regions with strong ICT foundations, granting them the autonomy to experiment and innovate while maintaining alignment with national goals. By focusing resources on regions with proven technological capabilities, China enhances the likelihood of successful AI adoption and diffusion. The positive selection of these regions, combined with their ability to recombine existing knowledge into new applications, reinforces their role as key drivers of AI innovation. This strategic approach ensures that regional strengths are harnessed to fuel both local advancements and national leadership in AI. Thus, we propose the following hypothesis:

H1. *Regional ICT specialization generates higher AI regional patenting performance in the candidate regions for AI development zones.*

2.2. Negative knowledge spillovers and regional competition

Regional innovation is shaped by the inter-regional knowledge spillovers of its neighboring areas (Boschma et al., 2017), often arising through patenting and R&D activities in adjacent regions (Moreno et al., 2005). While knowledge can spread through both intentional and unintentional channels (Antonelli and Colombelli, 2017), recent studies have started to address a research gap highlighting the negative side of innovation interactions between regions (Wang et al., 2022). As Montmartin et al. (2018) highlight, spatial dependencies can generate positive spillover effects through the sharing of knowledge but also exacerbate negative effects, such as market rivalry and competition for technological advantage between regions, leading to a redistribution of innovation resources. This tension is particularly pronounced in AI, where spillovers do not operate in the same way as in other technology sectors. Unlike traditional innovations, AI's development is deeply reliant on large-scale data success, specialized computational infrastructure, and high-skilled labor, which are often concentrated in a few leading regions (Cockburn et al., 2019). As a result, rather than promoting broad-based innovation, AI spillovers can reinforce existing regional disparities by disproportionately benefiting regions with superior access to these critical resources. Market rivalry in AI further exacerbates this dynamic, as regions compete not just for patents and talent but also for the underlying data that fuels AI advancements (Klingenberg et al., 2019). This differs from other sectors, where spillovers often lead to cumulative knowledge diffusion, whereas in AI, competition over exclusive data access and algorithmic advancements can limit the extent to which neighboring regions benefit from one another's progress. Consequently, while inter-regional competition may drive incremental innovation, it can simultaneously constrain breakthrough advancements in AI, shaping an innovation landscape where proximity does not necessarily translate into shared progress (Byun et al., 2021; Drivas, 2021).

The Chinese framework presents a unique subject for analyzing inter-regional competition. Despite being governed by a single-party system, the 34 administrative regions present different access to resources and socio-economic conditions (Wei, 2000). China's decentralization during the reform era that started in the 1970s gave local governments control over spending, resulting in intense inter-regional competition for markets and resources and a strong protectionism approach (He et al., 2008). This decentralization encouraged regional governments to focus on local industries and innovation systems, which has led to fragmented policy diffusion and resistance to centralized directives as regions prioritize their own interests (Gu, 2016). This competition has led to significant regional divergence in innovation outcomes. Some regions, particularly those with stronger institutional environments and market conditions, have been able to attract more resources and talent, creating a feedback loop of increasing innovation performance (Gao et al., 2021). Jimenez-Moro et al. (2023) provide evidence of innovation convergence clubs, where regions with better institutional frameworks cluster together and outperform their neighbors leading to varying levels of patenting activities (Wang et al., 2015) and innovation misallocation (Li et al., 2017). Within this competitive framework, Chinese local governments effectively utilize market forces to attract and sustain industries that complement their existing capabilities, encouraging regional specialization (He et al., 2018). This, however, increases inter-regional competition, as regions race to capture limited resources and position themselves as leaders in particular sectors since local governments are incentivized to protect their knowledge and resources from competitors, inhibiting positive knowledge spillovers (He et al., 2018).

The role of institutional proximity is critical in these dynamics. Differences in institutional proximity limit inter-regional knowledge transfer, with varying regional governance structures preventing effective collaborations (He et al., 2019). Cao et al. (2019) emphasize the importance of both geographical and institutional proximity for effective inter-organizational collaboration, but in the Chinese context, these proximities are often unevenly distributed, exacerbating inter-regional innovation gaps. Furthermore, when the central government focuses on a significant industrial project or technology program in one province, neighboring regions may reduce their own investments, leading to a crowding-out effect (Wang et al., 2022). In such cases, the central government's focus on a particular region exacerbates inter-regional disparities, as surrounding regions invest less, perceiving diminished returns on their innovation efforts. Moreover, as found also in studies applied in Europe, local competitive policies may act as a "beggar--thy-neighbor" strategy, redistributing innovation resources from one region to another and intensifying the uneven competition for resources (Lehmann and Menter, 2018). The effectiveness of local government reforms and support structures plays a crucial role in determining regional innovation performance. Regions that have embraced institutional reforms and aligned their innovation strategies with market demands have shown higher levels of innovation, while those lagging in reforms face further constraints in a highly competitive inter-regional environment.

Therefore, while knowledge spillovers often benefit innovation, the inter-regional competition for AI-related resources may lead to negative spillover effects, diminishing the innovation performance of neighboring regions. This competition, driven by both market rivalry and resource misallocation, reinforces regional disparities and limits the

diffusion of technological advancements, particularly in high-tech sectors like AI. All this considered, we propose the following research hypothesis:

H2. *Regional AI patenting performance generates negative knowledge spillovers to neighboring regions.*

3. Data, variables and methodology

3.1. Data sources

We conduct the empirical analysis on 30 Chinese provincial-level regions[1] observed over the period 2006–2021. The starting year is chosen because of the introduction of the "2006 Plan" which is widely recognized as a turning point in China's innovation journey (Liu et al., 2011). We collected patent data from the *Orbis Intellectual Property Database* and the *Annual Report of Patent Statistics.* Then we collected provincial-level regions' administrative data from the *China Statistical Yearbook* and the *China Statistical Yearbook on Science and Technology*[2], which are all datasets previously and effectively used in empirical studies applied to China (Chen et al., 2018; Ma et al., 2023; Wang et al., 2022; Wei, 2022).

3.2. Variables

3.2.1. Dependent variable

We measure provincial-level regions' AI patenting performance in terms of patents applied to the China National Intellectual Property Administration (CNIPA). By relying on variables derived from Chinese domestic patent data, the study ensures comparability between regions. Consequently, these variables serve as consistent measures of both technologically and economically significant innovations across the provincial-level regions under examination (Acs et al., 2002). Our analysis concentrates on patent applicants, driven by the complexities of identifying inventors in China. The CNIPA lacks consistent documentation of inventor details (Yin et al., 2020), and the homonym problem complicates the disambiguation of Chinese names, a widely recognized challenge in disambiguation methodologies (Li et al., 2014; Yin et al., 2020). While acknowledging this limitation, previous studies have successfully utilized applicants' locations rather than the inventors' to conduct their analysis (Kroll, 2016; Suzuki, 2023).

Within the term "AI" there can be found different technologies (Cockburn et al., 2019), making the identification of what can be included within the label discussed in the literature (Benassi et al., 2022). However, there are different ways in which AI can be codified and identified which have been used in the literature. We followed the search strategies used by Liu et al. (2021), Liu et al. (2021)) that rely on the union of selected keywords in the title, abstract or claim, IPC and CPC codes (expressed in Boolean terms as: keywords OR IPC codes OR CPC codes).[3] The data are only limited to invention patents. Design patents and utility model patents are excluded due to their lower inventive step, attributed to their legal characteristics (Huang, 2017). For each AI-related patent, we collected the application date to the CNIPA and the applicants' information on their regions of affiliation. Then, we computed the sum of AI-related patents for each region i and year t by partly attributing patents that list applicants from different regions (fractional counts). Fig. 1 reports the regional average distribution between 2006 and 2021 of AI-related patents per population.

3.2.2. Independent variable

Our independent variable is regional specialization in ICT, proxied by Revealed Technological Advantage (RTA) measured for each provincial-level region. RTA is an index that measures the relative technological strength (or weakness) of the regions (Soete, 1987) and is a proxy of regional specialization in a technological field. We compute RTA by considering ICT-related patents since the knowledge base of such technology influences the emergence of AI and since AI represents developments of the ICT system (Igna and Venturini, 2023; Xiao and Boschma, 2022). ICTs themselves are often regarded as GPTs, and a substantial knowledge base in ICTs not only fosters high-tech innovation but also acts as a catalyst for regional innovation (Sergio et al., 2023). Hence, we collected ICT-related patents applied to CNIPA by using specific IPC codes following Inaba and Squicciarini (2017)[4] and we retrieved the applicants' information on their regions of affiliation, and we computed the sum of ICT-related patents for each region i and year t by partly attributing patents that list applicants from different regions (fractional counts). Then, we collected the total amount of patents applied to CNIPA in each region i at year t. RTA in ICT is computed as follows:

$$RTA\ ICT = \frac{ICT\ patents_{i,t} / Totalpatents_{i,t}}{\sum_{i=1}^{30} ICTpatents_{i,t} \Big/ \sum_{i=1}^{30} Totalpatent_{i,t}}$$

where the numerator represents the share of ICT-related patents on total patents for region i at time t, while the denominator represents the share of ICT-related patents on total patents calculated as the sum of the 30 regions in our sample. RTA index varies around unity, such that values greater than 1 observed at the time t indicate that region i is relatively strong in the ICT technological field, compared to other regions and the same technological field, while values less than 1 indicate relative weakness. Since the RTA index could yield biased estimates related to its skewed distribution and the violation of the normality assumption of the error term in the regression, we standardize the index to make the distribution close to a normal one as proposed by Colombelli, Krafft, and Quatraro (2014). Moreover, the RTA index may suffer from the volatility of patent statistics, hence we use a three-year moving average to attenuate this source of distortion and to smooth the erratic trend of the flow of patents.

Then, we followed Acemoglu and Restrepo's (2020) technological frontier instrumental variable strategy to identify regional specialization in ICT. By adapting their study, we constructed the instrument in three steps. First, we instrument China's provincial-level RTA in ICT using an analogous measure constructed for the federal states of the United States of America (US), based on USPTO patent data, as the US represents the country that sets the bar for the global advancements in ICT patents. Second, we compute the average of RTA in ICT across the US federal states of California, Massachusetts, New York, Texas and Washington, which are the 5 US states with the highest number of ICT applications and together account for approximately 70 % of the ICT applications submitted to the USPTO by US-based applicants during the period 2006–2021.[5] Focusing on foreign federal states representing the technological frontier in ICT allows us to filter out regional specialization in ICT due to idiosyncratic and unobserved Chinese regional characteristics (e.g., governance quality and policy interventions) and to isolate the source of variation related to global technological advancement in ICT. Third, to focus on historical and persistent differences in the ICT specialization across Chinese regions, we use the share of Scientists and

[1] Provincial-level regions are composed by 22 provinces, 4 municipalities, and 4 autonomous regions of the People's Republic of China. Tibet is excluded for lack of data.

[2] Economic aggregates are expressed in Yuan at constant 2015 prices. The *Annual Report of Patent Statistics,* the *China Statistical Yearbook* and the *China Statistical Yearbook on Science and Technology* are all issued by the National Bureau of Statistics of China.

[3] Search strategy is summarized in Appendix 1.

[4] Search strategy is summarized in Appendix 1.

[5] Appendix 2 reports the ICT patent applications of California, Massachusetts, New York, Texas and Washington over the ICT patent applications in US

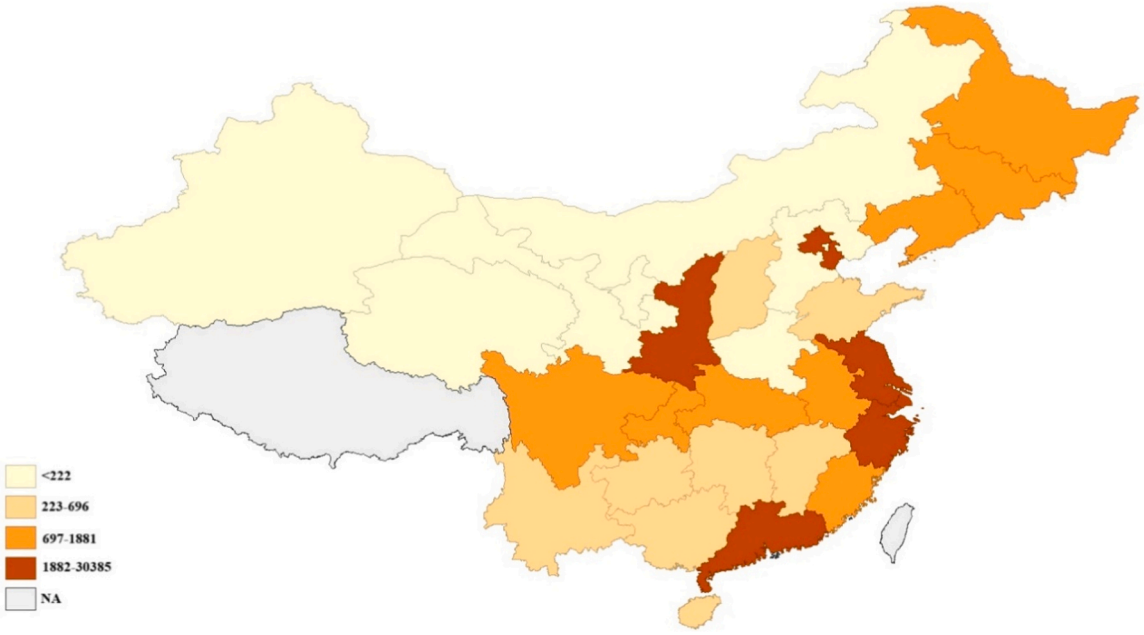

Fig. 1. Quartile distribution of 2006–2021 average patent per million population.

Engineers as a percentage of the total number of personnel involved in Science and Technology (S&T) activities in 1997[6] to weight the US federal states' RTA in ICT. This measure serves two purposes: on the one hand, the share of Scientists and Engineers in 1997 is a proxy for the historical capacity of Chinese regions to absorb and develop new technologies; on the other hand, by weighting the average of US federal states' RTA in ICT with this historical measure, we capture the extent to which Chinese regions were predisposed to specialize in ICT. Hence, the IV is given by the following formula:

$$IV\ RTAICT_{i,t} = \frac{Scientists\ and\ Engineers_{i,\ 1997}}{S\&TPersonnel_{i,\ 1997}} \times \overline{US\ RTA\ ICT}_{i,t}$$

While acknowledging significant US-China ICT investment flows, the potential for direct technology transfer, and the interdependent nature of global technology development where US and Chinese innovations influence each other, we argue that our instrument captures the exogenous trend of US-originating technological advancements, which influences Chinese regional ICT specialization, and we mitigate potential confounding effects through control variables in our regressions, isolating the effect of US ICT specialization as a leading indicator.

In addition, to understand whether regional specialization in ICT generates stronger AI regional patenting performance in the candidate regions for AI development zones, we rely on the interaction between regional specialization in ICT and a dummy variable that takes the value 1 when the region is a candidate for AI development zones and 0 otherwise. Fig. 2 highlights the 15 Chinese provincial-level regions that developed AI zones.

3.2.3. Control variables

Then, we introduce a set of control variables. As a proxy for regional knowledge, we focus on intramural high-tech R&D expenditures of Chinese-owned enterprises rescaled for GDP to control for the different economic sizes of each region. Since the early 2000s, high-tech companies have been pivotal in China's pursuit of becoming an innovation-driven nation (Chen et al., 2018). These companies have significantly contributed to the growth of emerging industries, particularly the new-generation IT sector, by actively engaging in activities such as building ICT infrastructure, advancing R&D commercialization and industrialization, and acquiring technology (Li et al., 2021).

We also measure the ratio between employees in high-tech industries and total employees of a region, as a proxy for the endowment of regional human capital, which fosters, adopts, and diffuses technological change (Nelson and Phelps, 1966), but also it absorbs and imitates foreign advanced technologies (Verspagen, 1991). Xie et al. (2018) have found that there are positive relationships between the absorptive capacity of Chinese high-tech companies and their ability to innovate. They specifically underline how the dimensions of knowledge transformation and knowledge exploitation play a pivotal role in cultivating core competencies. In line with Furman et al. (2002), we also introduce GDP per capita to assess the capability of a region to convert its internal knowledge stock into an accomplished regional of economic and technological development. Moreover, knowledge flows can arise from foreign direct investment (FDI) (Coe and Helpman, 1995), hence, we introduce the share of FDI per GDP. This is particularly relevant in the case of China, which has greatly benefited from international knowledge diffusion in building its initial technological capabilities (Fu and Hou, 2021). An overview of the variables, the descriptive statistics, and the correlation matrix are provided in Table 1.

3.3. Methodology

To empirically investigate the impact of regional specialization on Chinese regional AI patenting performance, we estimate the following empirical model:

$$Y_{i,t} = \alpha + \beta_1 RTA\ ICT_{i,t-1} \times AIzone + X'_{i,t-1}\beta + u_i + \iota_t + \varepsilon_{i,t} \quad (1)$$

where Y represents the output of regional AI patenting performance, proxied by AI-related patents per million population. *RTA ICT* measures the regional technological specialization in ICT, *AIzone* indicates whether a region is a candidate for an AI development zone, and $X'_{i,t-1}$ is a vector of control variables, such as the share of high-tech R&D expenditure on GDP, the share of high-tech R&D personnel on total employment, GDP per capita, and the ratio of FDI on GDP. $\varepsilon_{i,t}$ assesses

[6] Data on S&T activities for China's 30 provincial-level regions start in 1997, the year Chongqing was established as an autonomous municipality. Therefore, the analysis cannot go back further, as the region's administrative status was not distinct before this year.

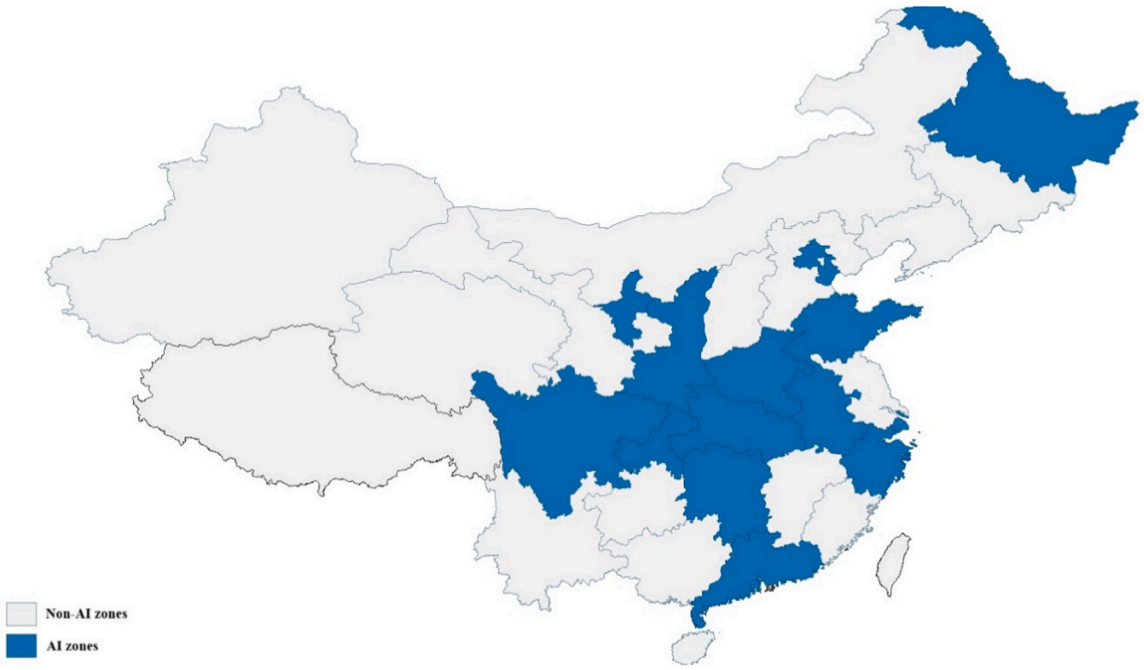

Fig. 2. Chinese provincial-level regions with established AI zones.

Table 1
Variable sources, descriptive statistics and correlation matrix.

Section A - Variables description and sources						
Description		Abbreviation	Sources			
Log of total AI-related patents per million population		AIpat/Pop	Orbis Intellectual Property Database, China Statistical Yearbook			
3 years MA Revelead Technological Advantage in ICT		RTA ICT	Orbis Intellectual Property Database, Annual Report of Patent Statistics			
Log of High-tech industry R&D expenditures on GDP		HTRDexp/GDP	China Statistical Yearbook on Science and Technology, China Statistical Yearbook			
Log of High-tech industry R&D personnel on total employment		HTRDpers/Emp	China Statistical Yearbook on Science and Technology, China Statistical Yearbook			
Log of GDP per capita		GDP/Pop	China Statistical Yearbook			
Log of FDI on GDP		FDI/GDP	China Statistical Yearbook			
Section B - Descriptive statistics						
	Observations	Mean	SD	Min	Max	
AIpat/Pop	450	5.41	2.54	0	11.5	
RTA ICT	450	−0.33	0.34	−0.93	0.46	
HTRDexp/GDP	450	6.13	0.4	5.18	7.16	
HTRDpers/Emp	450	−3.53	0.88	−5.36	1.17	
GDP/Pop	450	−2.37	1.49	−9.14	0.52	
FDI/GDP	450	−3.82	1.45	−9.93	−0.03	
Section C - Correlation matrix						
	AIpat/Pop	RTA ICT	HTRDexp/GDP	HTRDpers/Emp	GDP/Pop	FDI/GDP
AIpat/Pop	1.0000					
RTA ICT	0.4984	1.0000				
HTRDexp/GDP	0.8037	0.5247	1.0000			
HTRDpers/Emp	0.2479	0.2031	0.3924	1.0000		
GDP pc	0.5905	0.4546	0.5544	0.1235	1.0000	
FDI/GDP	0.4689	0.2879	0.4484	0.1543	0.6186	1.0000

the non-measured determinants of output and productivity, while to account for the panel structure of the data, we augment the model with fixed effects, where u_i is the region fixed effect for region i and ι_t captures the time fixed effect. Both region and time fixed effects sort out from the model specification any unobserved factor that might hinder identification related to time-invariant characteristics of the region and potential trends existing in a specific year for all regions. The independent variables are lagged one year to mitigate endogeneity problems, and we also estimated two-stage least squares (2SLS) regressions to consistently estimate regional specialization in ICT.

We then draw on spatial econometrics by relying on spatial spillovers to proxy for competition and institutional differences between regions, captured by the spatial lag of the dependent variable. We build upon a quadratic inverse distance matrix calculated from the latitude and longitude of each region's capital where the general element w_{ij} indicates that region i is spatially connected to region j. The inverse of the quadratic inverse distance between each pair of regions is used to account for the intuition that closer regions are more related than more distant regions and to emphasize the role of nearest neighboring competition related to institutional differences.

Firstly, we perform the robust Lagrange Multiplier test for spatial lag dependence and spatial error dependence proposed by Elhorst (2014). The results of the LM tests indicate spatial lag dependence but rule out spatial error dependence. Then, we perform a Spatial Autoregressive Model (SAR) and a Spatial Durbin Model (SDM) through Maximum Likelihood to estimate the spatial spillover effects of AI patenting performance on neighboring regions. Our theoretical framework suggests that the spatial spillovers of AI patenting performance primarily occur

through a spatial autoregressive diffusion process itself, rather than through the spatial spillovers of the independent variables. Therefore, the SAR model, which directly captures spatial autoregressive spillovers, should be preferred. Consequentially, by following Agiakloglou and Tsimpanos (2021, 2023), we compare the performance of the spatial models in terms of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics. As reported in Table 2, SAR performs better than SDM both in terms of AIC and BIC. We can conclude that the SAR model is the best specification to estimate the spatial spillover effects of AI patenting performance on neighboring regions, while the SDM, by including spatial lags of the independent variables, introduces unnecessary complexity without significantly improving model fit, as evidenced by the higher AIC and BIC values.

Moreover, we need to identify the spatial lag term $WY_{i,t}$ and the variable that proxies regional specialization in ICT due to correlation with the error term $\varepsilon_{i,t}$. We deal with the simultaneity bias by applying a control function (CF) approach. Firstly, we run the regression to identify the spatial lag term $WY_{i,t}$, as follows:

$$WY_{i,t} = \beta_0 + Q'_{i,t}\beta + \nu_{i,t}^{spatial\ lag} \tag{2}$$

where $Q'_{i,t}$ is a vector that contains all exogenous variables included in the model and their spatial lags, in line with Kelejian and Prucha (1997), and $\nu_{i,t}^{spatial\ lag}$ assesses the non-measured determinants of spatial spillovers. Then, to control for the endogeneity of RTA in ICT, we run the following regression:

$$RTA\ ICT_{i,t} = \beta_0 + \pi Z_{i,t} + X_{i,t}'\beta + \nu_{i,t}^{RTA\ ICT} \tag{3}$$

where Z is the technological frontier instrumental variable, $X_{i,t}'$ is the vector of control variables, and $\nu_{i,t}^{RTA\ ICT}$ assesses the non-measured determinants of regional specialization in ICT.

Finally, the residuals $\nu_{i,t}^{spatial\ lag}$ and $\nu_{i,t}^{RTA\ ICT}$ are included in the SAR equation to control for the endogeneity of $WY_{i,t}$ and $RTA\ ICT_{i,t}$:

$$Y_{i,t} = \beta_0 + \rho WY_{j,\ \ t} + X'_{i,t-1}\beta + \gamma_1 \nu_{i,t}^{spatial\ lag} + \gamma_2 \nu_{i,t}^{RTA\ ICT} + u_i + \iota_t + \varepsilon_{i,t} \tag{4}$$

where ρ collects the spatial spillovers of AI patenting performance of neighboring regions generated by the quadratic inverse distance matrix W, $X'_{i,t-1}$ is a vector of control variables, while $\nu_{i,t}^{spatial\ lag}$ and $\nu_{i,t}^{RTA\ ICT}$ control for the endogeneity of the spatial lag and regional specialization in ICT.

4. Results and discussion

In this section, we present our econometric results and assess the economic significance of the estimated effects of regional specialization in ICT and inter-regional knowledge spillovers on AI patenting performance.

4.1. Linear regression results

Table 3 displays the results of the linear panel model with fixed effects and the 2SLS. Column 1 shows the results of the regression without the interaction between RTA ICT and AI zones as a baseline model. The coefficient of RTA ICT is positive and statistically significant ($\beta = 0.2964$, $p\text{-value} < 0.05$), which reveals that regional specialization in ICT is positively correlated with AI patenting performance. Column 2 reports the results of the regression shown in Eq. 1. We find that the coefficient of RTA ICT of regions with AI zones is positive and statistically significant ($\beta = 0.3302$, $p\text{-value} < 0.01$), while the coefficient of regions without AI zones is still positive, but not significant ($\beta = 0.2059$, $p\text{-value} > 0.1$). Then, we performed a 2SLS model. In Column 3 we find a statistically significant correlation between IV and the independent variable ($\beta = -0.1385$, $p\text{-value} < 0.1$; $\beta = 0.4535$, $p\text{-value} < 0.01$). Finally, Column 4 reports the regression results of 2SLS. In the 2SLS model, RTA ICT is positive and statistically significant for regions with and without AI zones ($\beta = 0.6705$, $p\text{-value} < 0.01$, and $\beta = 0.4984$, $p\text{-value} < 0.01$, respectively). The magnitude of the coefficient is higher for regions with AI zones, thus confirming H1. Moreover, the difference in magnitude between the OLS and 2SLS estimates for both the RTA ICT × no AIzone and RTA ICT × AIzone interaction term suggests that the OLS estimates reported in Column 2 were downward biased due to potential endogeneity. Specifically, OLS may underestimate the effect due to measurement error in ICT specialization, omitted variables related to regional innovation capacity, or reverse causality, where regions with stronger AI activity also enhance their ICT capabilities over time. The 2SLS reported in column 4 corrects for these biases, revealing a stronger positive effect of ICT-related specialization in both groups of regions with respect to OLS. This suggests that the role of ICT in AI-driven regional innovation is even more pronounced than initially estimated, reinforcing the importance of ICT capabilities in fostering AI development, especially in AI zones.

These results offer an explanation for the rationale behind establishing the AI development zone policy, emphasizing that these specific

Table 2
Robust Lagrange Multiplier Test and Model fit.

	Linear	SAR	SDM
RLM Lag	155.61***		
RLM Error	1.861		
AIC	−24.547	−27.61	−20.247
BIC	16.936	17.964	75.618

Table 3
Linear OLS Fixed effects model estimation results.

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
			First stage	Second stage
	AIpat/pop	AIpat/pop	RTA ICT	AIpat/pop
RTA ICT	0.2964**			
	(0.1372)			
IV RTA ICT				
RTA ICT*AI zones:				
1) NO AI zones		0.2069		0.4984***
		(0.4183)		(0.0984)
2) AI zones		0.3302***		0.6705***
		(0.0982)		(0.1902)
IV RTA ICT*AI zones:				
1) NO AI zones			−0.1385*	
			(0.0758)	
2) AI zones			0.4535***	
			(0.0872)	
HTRDexp/GDP	0.0574	0.0573	0.0755***	0.0431
	(0.0905)	(0.0904)	(0.0158)	(0.1282)
HTRDpers/Emp	0.0449	0.0447	0.0225**	−0.0804
	(0.0337)	(0.0336)	(0.0109)	(0.0837)
GDP/Pop	3.7587***	3.8128***	0.1463***	1.0416***
	(0.5556)	(0.5793)	(0.0474)	(0.3433)
FDI/GDP	0.1557	0.1515	0.0062	0.0273
	(0.2004)	(0.1995)	(0.0199)	(0.1170)
Constant	−16.8174***	−17.1826***	−1.0028***	2.9772
	(3.4133)	(3.5489)	(0.3405)	(3.105)
Regional fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Observations	420	420	420	420
F-stat NO AI zone			45.56	
F-stat AI zone			18.43	
R2	0.9465	0.9465	0.4116	0.5920

Robust standard errors are in parentheses *** p < .01, ** p < .05, * p < .1

provinces exhibit a heightened patenting performance in AI due to their previous specialization in ICT. This aligns with previous literature on the role of HTDZs in promoting and diffusing innovation (Howell, 2019), which also underscores the economic development diversity that has historically been present in China (Fu et al., 2021). Moreover, these findings underscore the role of positive selection in Chinese policy, as described by Wang and Yang (2021), wherein regions with strong pre-existing technological capabilities are chosen as AI zones, leading to a "picking the fittest" approach in the Chinese regional AI development. However, this specialization can also generate reinforcing cumulative advantages, where regions initially benefiting from ICT specialization attract additional AI-related investments over time, further deepening their technological lead (De Propris and Bailey, 2021; Montresor and Quatraro, 2017). This suggests that spatial path dependencies and knowledge cumulativeness (Corradini et al., 2021) contribute to the observed patterns, as past innovation activities significantly influence future specialization trajectories (Boschma et al., 2017).

4.2. Spatial panel regression results

Table 4 reports the results of the SAR model and control function approach. Column 1 shows the results from the SAR estimation, which shows a negative and statistically significant coefficient of the spatial lag of AI patenting performance ($\beta = -0.2162$, *p-value* < 0.05). Hence, an increase in AI patenting performance in neighboring regions negatively affects AI patenting performance in the focal region, suggesting the existence of negative spillover effects and competition among Chinese provincial-level regions. Then, we report the estimation of the control function approach to identify the effects of the spatial lag and RTA ICT. Columns 2 and 3 show the results of the first step of the control function approach for spatial lag and RTA ICT, respectively. Then, Column 4 reports the results for the second step of the control function, in which we control for the endogeneity of the spatial lag and RTA ICT. Both the residuals $\nu_{i,t}^{spatial\ lag}$ and $\nu_{i,t}^{RTA\ ICT}$ are statistically significant ($\beta = 0.0808$, *p-value* < 0.05, and $\beta = 0.8821$, *p-value* < 0.1, respectively), hence our SAR model is able to identify the spatial spillovers of neighboring AI patenting performance and regional specialization in ICT ($\beta = -0.2064$, *p-value* < 0.05, and $\beta = 0.3213$, *p-value* < 0.05, respectively), leading us to confirm H2.

Table 4
SAR model estimation results.

	(1) SAR	(2) OLS First step - CF	(3) OLS First step - CF	(4) SAR Second step - CF
	AIpat/Pop	WY	RTA ICT	AIpat/Pop
WY	−0.2162**			−0.2064**
	(0.0967)			(0.0965)
RTA ICT	0.2931*			0.3213**
	(0.1560)			(0.1555)
IV RTA ICT		−0.7613	0.8686***	
		(0.6648)	(0.2866)	
W IV RTA ICT		−.0.7325***		
		(1.057)		
HTRDexp/GDP	0.0579	0.2755***	0.0532**	0.0731
	(0.0698)	(0.0551)	(0.0231)	(0.0695)
HTRDpers/Emp	0.0479	0.0503	0.0162	0.0429
	(0.0299)	(0.0308)	(0.0121)	(0.0298)
GDP/Pop	3.7637***	0.1366	−0.0013	3.8224***
	(0.6074)	(0.4842)	(0.2009)	(0.6042)
FDI/GDP	0.1635	0.2752***	0.0049	0.1652
	(0.1257)	(0.0814)	(0.0344)	(0.1252)
W HTRDexp/ GDP		1.4419***		
		(0.0809)		
W HTRDpers/ Emp		0.1075		
		(0.0775)		
W GDP/Pop		4.3399***		
		(0.7735)		
W FDI/GDP		1.2553***		
		(0.1082)		
Residuals Spatial Lag				0.0808 * *
				(0.0400)
Residuals RTA ICT				0.8221 *
				(0.4222)
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Observations	420	420	420	420
R2	0.588	0.931	0.098	0.585
AIC	−27.6	−1020.61	−1041.18	−31.2
BIC	−3.3	−979.52	−1020.63	1.07

Robust standard errors are in parentheses *** p < .01, ** p < .05, * p < .1

Negative inter-regional spillovers may exacerbate the technology and innovation gap between regions in developing AI, which could also hamper AI patenting performance at the national level. While regional specialization can drive localized technological leadership, our findings suggest that it also intensifies market rivalry, resource concentration, and uneven knowledge diffusion, which in turn constrain breakthrough innovation at the national level (Montmartin et al., 2018). These negative spillovers could undermine the potential for inter-regional knowledge recombination—a key mechanism in fostering the radical innovation necessary to advance along the technological frontier, particularly in AI, a GPT with widespread transformative potential (Cockburn et al., 2019). The fragmentation of AI capabilities across regions may diminish opportunities for such recombination, slowing the pace at which China advances toward the technological frontier. While competition among AI-leading regions can fuel incremental progress, it may also undermine collaborative innovation dynamics that are crucial for major technological breakthroughs (Byun et al., 2021). The observed negative spillovers suggest that inter-regional AI competition is more likely to lead to duplication of efforts rather than productive knowledge-sharing, particularly if leading regions prioritize self-sufficiency over cooperation (Bloom et al., 2013). Specifically, these spillovers may take distinct forms. First, resource crowding may occur when regions compete for limited R&D funding and skilled talent, generating a dynamic in which one region's gain comes at the expense of another's innovation capacity (Montmartin et al., 2018; Wang et al., 2022). Second, strategic isolation may arise when regions, in their pursuit of self-sufficiency, limit opportunities for cross-regional knowledge recombination, hindering collaborative efforts that are vital for breakthrough innovations (Montmartin et al., 2018). Third, institutional lock-in may develop as regions become entrenched in their existing development paths due to historical specialization, making it difficult to diversify and adapt to emerging technologies. Such over-specialization creates self-reinforcing cycles in regional innovation systems, making it difficult for local actors to diversify or adopt new technologies (Tödtling and Trippl, 2005). In the context of AI development, this lock-in may prevent even leading regions from transitioning toward more innovative, collaborative, or diversified technological trajectories (De Propris and Bailey, 2021). Yet, regional lock-in is not deterministic since proactive policies can foster regional renewal and counteract excessive specialization through entrepreneurial and institutional agency (Newey and Coenen, 2022). Corradini (2019) further emphasizes the role of local knowledge bases and institutional support as critical determinants for technological entry, suggesting that while specialization provides a foundation for new technology development, it can also reinforce disparities unless regions broaden their capability portfolios.

Such disparities are particularly concerning for a country like China, where the government's independent innovation strategy emphasizes the need for technological self-sufficiency and national competitiveness (Chen et al., 2018). The focus on AI may require stronger attention to the

development of absorptive capacities of lagging regions, something that has historically been overlooked in the Chinese regional innovation approach (Zhang and Rodríguez-Pose, 2024). If left unaddressed, the uneven geography of AI development could weaken China's position in the global AI race by limiting the full mobilization of its domestic innovation potential. Given these risks, our findings call for a shift toward a more coordinated AI policy framework that balances specialization with inter-regional integration. While regional AI zones have helped concentrate resources in key hubs, ensuring cross-regional collaboration and capacity-building mechanisms will be essential to mitigate the unintended consequences of regional competition (De Propris and Bellandi, 2021). In Section 5, we discuss targeted policy interventions that could help strengthen knowledge diffusion, institutional proximity, and absorptive capacities across China's AI regions, ensuring that specialization-driven advancements contribute to an inclusive and globally competitive AI innovation ecosystem.

4.3. Robustness check

To ensure robustness of these findings, we replicate the models by replacing the dependent variable with AI patents that meet the search strategy as the intersection between keyword in the title, abstract or claim, and IPC or CPC codes (expressed in Boolean terms as: keywords AND [IPC codes OR CPC codes]). Table 5 reports the results for the linear panel model and the SAR regression of the robustness analyses. The results are consistent with our earlier findings presented in Tables 3 and 4.

Table 5
Robustness check estimation results.

	(1) OLS	(2) 2SLS Second stage	(3) SAR	(4) SAR Second step - CF
	AIpat/Pop	AIpat/Pop	AI pat/Pop	AIpat/Pop
RTA ICT*AI zones:				
0) NO AI zones	0.1609*			
	(0.0898)			
1) AI zones	0.2621*			
	(0.1482)			
IV RTA ICT*AI zones:				
1) NO AI zones		0.1127**		
		(0.0456)		
2) AI zones		0.2457***		
		(0.0873)		
WY			−0.3279***	−0.3199***
			(0.0905)	(0.0907)
RTA ICT			0.1754*	0.2347**
			(0.0893)	(0.0895)
HTRDexp/GDP	0.0155	0.1229***	0.0032	−0.0066
	(0.0373)	(0.0544)	(0.039)	(0.0395)
HTRDpers/Emp	−0.0124	−0.0285	−0.0138	−0.0192
	(0.0176)	(0.0307)	(0.0171)	(0.0169)
GDP/Pop	0.3842	0.3230	0.3578	0.4453
	(0.4391)	(0.1519)	(0.3476)	(0.3439)
FDI/GDP	0.0921	−0.0836	0.0539	0.0526
	(0.0561)	(0.0482)	(0.0719)	(0.0709)
Residuals Spatial Lag				0.1749*
				(0.1027)
Residuals RTA ICT				−0.2040**
				(0.1027)
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Observations	420	420	420	420
R2	0.874	0.400	0.341	0.336
F stat NO AI zone		45.56		
F stat AI zone		18.43		
AIC	297.7	1027.7	−492.7	−503.1
BIC	326.5	1113.9	−468.5	−470.8

Robust standard errors are in parentheses *** p < .01, ** p < .05, * p < .1

5. Conclusions, implications and limitations

In this study, we show the role of regional specialization in ICT and negative interregional knowledge spillovers in China's AI patenting performance by using multiple and reliable sources to construct a comprehensive dataset of 30 Chinese provincial-level regions from 2006 to 2021. Previous literature shows the importance of developing the right capabilities for successful specialization strategies in Industry 4.0 (Labory and Bianchi, 2021), whether these technologies widen the gap between leaders and laggards (Corradini et al., 2021) or promote the creation of new islands of innovation (Capello and Lenzi, 2021). We contribute to this debate by exploring the role of regional specialization in ICT and positive selection in fostering AI patenting performance, thereby further reinforcing the competitive advantage of specialized regions and widening the technological gap between regions that excel and those that lag behind. We also provide evidence of negative inter-regional spatial spillovers within Chinese regional AI patenting performance, contributing to the literature on inter-regional spillovers and their negative effects on innovation (Byun et al., 2021; Drivas et al., 2021). Then, we contribute to the literature by analyzing China's regional dimensions, which have been overlooked by regional analysis on AI (Capello and Lenzi, 2021; De Propis and Bellandi, 2021; Xiao and Boschma, 2022), despite its growing prominence in the AI domain and being a developing country.

Our findings have significant implications for policy-making. By limiting the diffusion of knowledge across regions, China risks not only exacerbating internal regional inequalities but also slowing down its progress toward global technological leadership. The strategy aims to mitigate these risks through targeted investments in regional innovation ecosystems, promoting intra-national collaborations to ensure that AI-driven growth is inclusive and maximizes national patenting and technological achievements. Aligning inter-regional innovation dynamics with indigenous innovation goals can enhance the country's capacity to leverage AI's GPT characteristics, secure long-term competitiveness, and maintain an upward trajectory within the global technological landscape.

To address these disparities, promoting inter-regional cooperation is imperative to strengthen the innovation outcomes of local contexts (Rong et al., 2021), and customized innovation policies are essential in achieving this alignment with the unique capabilities and requirements of each region (Brown, 2021). However, policymakers often choose to invest in the fittest region. While prioritizing the fittest may enhance regional competitiveness, it contributes to global and regional inequalities. The fittest regions, with technological advancements and flexibility, thrive, leaving the others behind. Given these dynamics, policymakers must consider a balanced regional development strategy that goes beyond focusing exclusively on leading AI zones. While investment in leading regions can drive AI breakthroughs, neglecting the lagging regions exacerbates the negative spillover effects we observed. We recommend policies that strengthen the absorptive capacities of lagging regions through targeted investments in education, R&D infrastructure, and institutional reforms. Drawing on the work of He et al. (2019) and Zhang and Rodríguez-Pose (2024), enhancing the institutional proximity of lagging regions to leading AI zones will enable them to absorb spillover benefits rather than suffer from market rivalry and resource crowding-out effects.

Our findings suggest that merely establishing AI development zones without fostering cross-regional collaboration may lead to inefficient resource allocation and redundancies. The evidence of negative spillovers implies that neighboring regions need targeted support to engage collaboratively and productively. Without intervention, market rivalry and resource concentration may further exacerbate regional disparities, limiting knowledge diffusion and reducing opportunities for breakthrough innovation (Montmartin et al., 2018; Bloom et al., 2013; Byun

et al., 2021). To mitigate these risks, we recommend the creation of AI Regional Collaborative Hubs, modeled after successful innovation ecosystems that link leading AI regions with adjacent lagging ones.

A key lesson from European innovation policy strategy is that competitive schemes often favor leading regions, whereas collaborative frameworks can reduce regional innovation gaps (Archibugi et al., 2022). Similarly, AI hubs should not merely intensify competition but actively promote cooperative strategies, such as cross-regional joint ventures, inter-regional funding schemes, and coordinated AI research clusters (De Propris and Bellandi, 2021). However, for these hubs to be effective, regions must possess a certain level of absorptive capacity, including technological capabilities, institutional quality, and human capital—factors critical to ensuring meaningful participation in innovation networks (Cohen and Levinthal, 1990; Filippetti and Zinilli, 2023).Aligning AI hubs with local strengths and complementary capabilities will help prevent the formation of exclusive innovation clubs, where only top-tier regions benefit while others remain excluded (Filippetti and Zinilli, 2023). Instead, structured collaboration mechanisms—such as shared R&D infrastructure, data-sharing platforms, and targeted talent mobility programs—can ensure that AI knowledge spillovers contribute to balanced regional development rather than reinforcing existing inequalities (Balland and Boschma, 2021; Capello and Lenzi, 2021). By embedding these principles into China's AI strategy, AI Regional Collaborative Hubs could serve as a model for promoting both technological leadership and regional cohesion, mitigating the risks of excessive competition while maximizing the potential of AI as a transformative general-purpose technology.

To summarize, while our study sheds light on the critical role of regional specialization and the negative effects of inter-regional spillovers in China's AI development, it also underscores the need for comprehensive policy interventions to mitigate regional disparities. To foster a more balanced and inclusive AI innovation development, policymakers must prioritize strengthening absorptive capacities in lagging regions, promoting regional collaboration, and adopting a stronger coordinated national strategy. This approach will help reduce the negative externalities of competition and ensure that all regions contribute to and benefit from China's AI advancement.

To conclude, we acknowledge that our study has certain limitations that should be addressed by future research. First, future work should analyze different AI innovation indicators, such as scientific publications, startup activity, and productivity related to AI. While patenting activity is generally a good proxy to measure innovation, it does not always capture everything. AI, in particular, is driven by data accumulation, algorithmic improvements, and large language models – many of which are not always patentable or are protected through trade secrets and copyrights. Second, while we employ fixed effects and an IV strategy to mitigate potential biases, we recognize that certain time-varying contextual factors, such as digital infrastructure quality and local policy interventions, could still play a role in shaping AI development. Future research could explore these dimensions further by incorporating high-frequency data on infrastructure investments, policy changes, and institutional frameworks to better disentangle their effects. Third, further investigation into the time-varying behavior of the effect of ICT specialization on AI performance is warranted. We encourage future research with more granular datasets (i.e., prefectural- or city-level data) to explore these variations in greater depth. Finally, our paper focuses exclusively on geographic proximity as a proxy for competition and institutional differences in influencing knowledge spillovers, so future research should broaden the scope by analyzing various channels that could facilitate or hinder knowledge diffusion, such as labor mobility, co-patenting, research and academic collaborations, and trade patterns. Finally, another strand of future research should also take a broader perspective and examine the contributions at a more granular level, such as prefecture and firm levels. However, these tasks are beyond the design and purpose of the present paper.

CRediT authorship contribution statement

Barabuffi Saverio: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cricchio Jacopo:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation, Conceptualization. **Di Minin Alberto:** Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.pirs.2025.100096.

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